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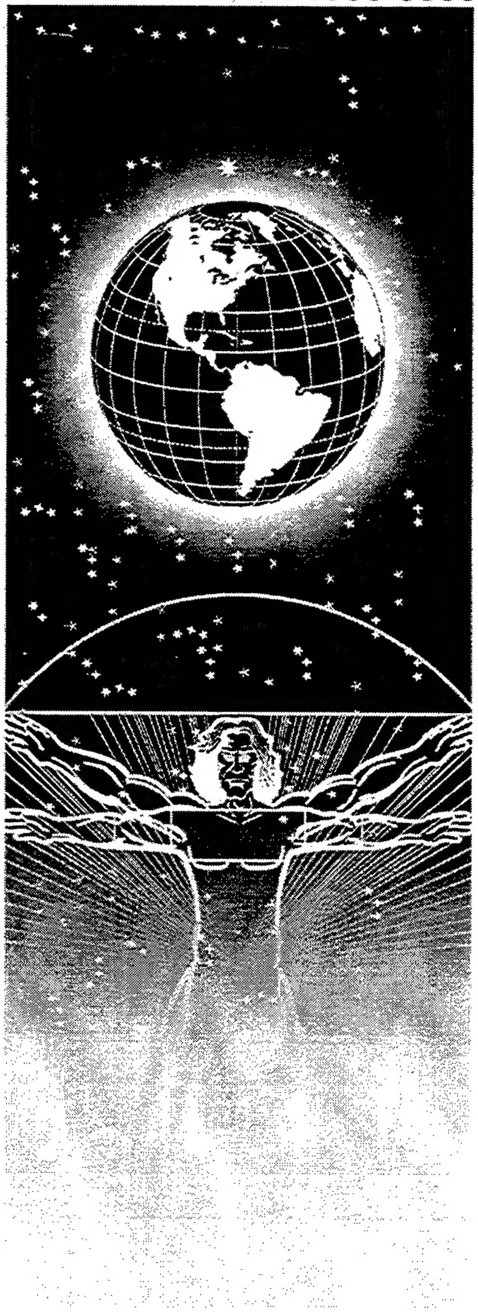

UNITED STATES AIR FORCE RESEARCH LABORATORY

STUDIES AND ANALYSES OF VULNERABILITIES IN AIDED ADVERSARIAL DECISION MAKING

James Llinas
Colin Drury
Wayne Bialas
An-che Chen

STATE UNIVERSITY OF NEW YORK AT BUFFALO
DEPARTMENT OF INDUSTRIAL ENGINEERING
BUFFALO, NY 14260-2050

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Human Effectiveness Directorate
Crew System Interface Division
2255 H Street
Wright-Patterson AFB OH 45433-7022

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FOR THE COMMANDER

Hendrick W Ruck

HENDRICK W. RUCK, PhD
Chief, Crew System Interface Division
Air Force Research Laboratory

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13. ABSTRACT *(Maximum 200 words)*

This report provides a preliminary examination of critical elements and processes involved in aided adversarial decision-making. The "aid" in the analysis (i.e., an automated decision aid) focuses upon a generic data fusion processor that estimates situation and threat states based on multisensor/multisource-based data assessments. In that frame of reference, this report provides a characterization of: (1) the information dependencies in data fusion processing, (2) the information dependencies in selected human-processing models, (3) the vulnerabilities of that information to Offensive IW attack, and (4) the processes of decision making. It also examines prototypical cultural and technological differences among hypothetical adversaries in order to identify the "value" a given adversary might place on specific information, and investigates the general nature of adversarial engagements in the context of a dynamic, two-sided, game-theoretic process.

The report recommends that two critical areas of research be continued: (1) the study and modeling of information dependencies, vulnerabilities, and notions of value in automated decision making processes, and (2) the better understanding and modeling of patterns of human trust in automation. A case study framework is recommended, and, if more than one case study is defined, then an examination of the potential reuse of knowledge about critical information dependencies and values may be conducted.

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PREFACE

Information has always been important, and even critical, in the conduct of war. That is, information ***in*** warfare has always been an important component for achieving victory. However, information-based warfare, or Information Warfare (IW), is a relatively new aspect of warfare and is largely a result of the major advances that have been made in various infrastructure technologies (solid-state devices, etc.) that have led to associated advances in sensing and computing technologies, as well as in advanced weaponry.

Within such Information Warfare environments, modern decision makers have at their service an ever-increasingly sophisticated set of automated decision-aiding/support tools. Nonetheless, they remain dependent upon both the availability and accuracy of the information provided, and the limitations of their own abilities to interpret that information. This report provides a preliminary examination of critical elements and processes involved in adversarial decision-making. The analysis focuses upon our postulated generic data fusion processor that estimates situation and threat states based on multisensor/multisource-based data assessments as the underlying decision aid. In that frame of reference, this report provides a characterization of: (1) the information dependencies in data fusion processing, (2) the information dependencies in selected human-processing models, (3) the vulnerabilities of that information to Offensive IW attack, and (4) the processes of decision making. It also examines prototypical cultural and technological differences among the current political powers and investigates the general nature of adversarial engagements in the context of a dynamic, two-sided, game-theoretic process.

The project was completed for the Air Force Research Laboratory's Information Analysis and Exploitation Branch (AFRL/HECA), under contract F41624-94-0-6000 for prime contractor, Logicon Technical Services, Inc. (LTSI). Work was accomplished under Work Unit Number 71841046, "Crew Systems for Information Warfare." Mr. Donald Monk was the Contract Monitor.

The authors offer special thanks to Mr. Gilbert Kuperman, of AFRL/HECA, the Work Unit Manager, for his initial interest, and for his ongoing support and direction which made this effort possible. The authors also wish to acknowledge Mr. Robert L. Stewart of LTSI, for his management of the project, and Ms. Elisabeth Fitzhugh, also of LTSI, for technical editing services.

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1. INTRODUCTION

For many of the world's societies, the onset of the Information Age is causing military theoreticians and strategists to reexamine basic premises, tactics, and doctrine associated with all phases of military operations, ranging from surveillance and reconnaissance to combat operations.

The nature of warfare is changing due to the explosion in the technical means of collecting, storing, analyzing, and transmitting information. The emergence of the Information Age presents new challenges to US strategy and organizational concepts. Technology not only brings our world closer together as information, money, and ideas move around the globe at record speed, but it also makes an open and free society even more vulnerable to disruptions within the information environment. The task reported on herein comprises a preliminary examination of the issues, considerations, and top-level models of one fundamental process that is inherent in the new paradigm of Information-based Warfare: the dependencies on, and vulnerabilities of, information in aided, adversarial decision making. The premise is that in Information Warfare (IW) environments modern decision makers, analysts, commanders, etc., each will have some suite/ensemble of automated decision-aiding/support tools, but will remain highly dependent on their own human-based abilities for final interpretation of decision aid-generated recommendations and hypotheses about "world states" or situations of interest. The decision-aiding tool postulated here is a generic data fusion (DF) processor that estimates situations and threat states of interest based on multisensor/multisource-based estimates. So we seek to characterize various aspects of this overall process, among other factors addressed herein:

- information dependencies in DF processing
- information dependencies in appropriate, representative human-processing models
- vulnerabilities of such information to representative offensive IW attacks
- decision making

Additionally, in this work, the intention is to integrate "representative" cultural and technological differences between the two adversarial sides of the generic model. We also look at the general nature of such adversarial engagements in the context of a dynamic, two-sided, game-theoretic process.

1.1 Top-level Perspectives on Information Warfare

The following is drawn from: (1) *USAF Doctrine Document 5: Information Warfare (AFDD 5; draft document, 2nd revision, Oct. 1996)*, provided to us by Mr. Gilbert Kuperman of AFRL/HECA and Mr. Robert Stewart of Logicon Technical Services, Inc., and (2) Dr. James Llinas' materials for a seminar he has been giving on IW for about 3 years. The evolving nature of the battlespace and emerging capabilities provide an unprecedented opportunity to achieve national strategic objectives short of war. New opportunities to observe and react to developing threats worldwide allow traditional military forces to evolve into lighter, more

responsive forces. Information Age technologies expand targeting opportunities for the decision maker, as well as the means of transmitting and storing information. The deterrent effect of an "information umbrella," where friendly forces use information to cause an adversary to comply with our will, has new and profound implications for the military.

Notwithstanding technological developments, ***the ultimate critical battlespace resides in, and has historically been, the mind of the adversary decision maker*** (*AFDD 5*, 1996, p. 9; emphasis is ours). IW enhances the military's ability to deter conflict by raising the cost to potential adversaries and thereby influencing their decisions. IW targets decisions by affecting directly or indirectly the flow of information into and out of the mind of the decision maker. By targeting the key decision makers, IW offers options to achieve our objectives more directly. Consequently, IW is not about technology, but about integrating information-related means to achieve common objectives.

In understanding the value added by IW, we must recognize the potential offered by emerging technologies and organizations concepts to take action in peacetime to defuse crises, or to multiply the effects of traditional military force application should deterrence fail. These new capabilities require a revised approach to the battlespace and the threat. While the process of Intelligence Preparation of the Battlespace (IPB) is not fundamentally different for IW, the nature of the battlespace is. Developing and understanding the information connectivity, the systems, and the human decision makers is a complex process. This battlespace is not defined by geography, nor is it always tangible in empirical ways. It crosses traditional political, economic, social, military, and infrastructure boundaries, complicating military operations.

1.2 Basic Principles of Information Warfare

IW is defined as actions taken within the information environment to deny, exploit, corrupt, destroy or assure information viability. The official DoD definition is, "actions taken to achieve information superiority in support of national military strategy by affecting adversary information and information systems while leveraging and protecting our own information and information systems." (Defense Science Board, 1994) The goal is to achieve an information advantage or "Dominant Battlespace Awareness" (DBA; another popular term evolving in the IW community), generally meaning, the ability to achieve perfect knowledge of the enemy's disposition, location, and orientation in a limited region without exposing friendly forces to high risk. IW can make a decisive difference at the strategic level by neutralizing an adversary's will and capacity to fight. If we consider the basic definition of warfare as being the set of all lethal and non-lethal activities taken to subdue the will of an adversary, then the extension of the role of IW as activity directed against any part of the knowledge and belief systems of an adversary—to support subduing him—is clear and logical. Szafranski and Stein have written about this notion in the *Airpower Journal*: "The target system of information warfare can include every element in the epistemology of an adversary...[meaning]...the entire 'organization, methods, and validity of knowledge.'" (Szafranski, 1995, p. 60); "...information warfare actions must be directed against both the adversary's knowledge systems and belief systems." (Szafranski, 1995, p. 60); "The target of information warfare is, then, the human mind...." (Stein, 1995, p. 32), and information

warfare involves the "manipulat[ion of] the multi-media, multisource fictive universe" (Stein, 1995, p. 34). These are the perspectives we have taken in this report.

IW can facilitate military efforts at the operational and tactical levels by enabling freedom of action, security, initiative, and flexibility. Information also can be considered as a "realm" within which the military operates, not unlike "air" and "space." By analogy (and much has been proffered regarding IW concepts by analogy to conventional warfare), one could then conceptualize Air Force missions such as *counterinformation*, with subordinate mission types such as *offensive counterinformation* and *defensive counterinformation.* The Air Force has, in various USAF doctrine documents, defined notions of *indirect* and *direct IW.* Indirect IW comprises those actions, currently defined as *command and control warfare (C2W),* that are involved in the general activity of perception management of an adversary's surveillance and reconnaissance systems (*i.e.*, the management of "external" information). C2W is "The integrated use of operations security (OPSEC), military deception, psychological operations (PSYOP), electronic warfare (EW), and physical destruction, mutually supported by intelligence, to deny information to, influence, degrade, or destroy adversary C2 capabilities, while protecting friendly C2 capabilities against such actions" (*JCS MOP 30,* 1993). Direct IW comprises those actions that some may call "Netwar"—such as viral software attacks, etc., directed at the "internal" information of an adversary. These notions are shown in Figure 1.2-1 below.

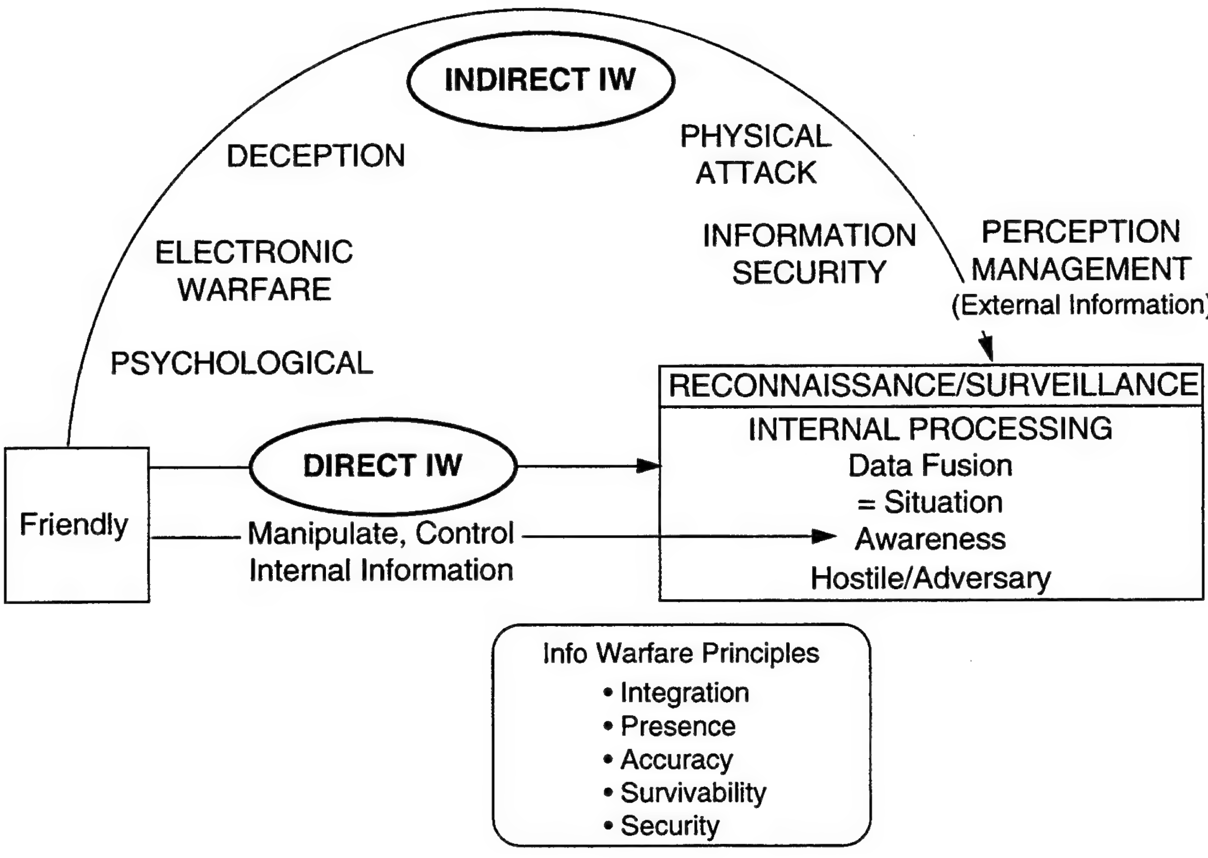


Figure 1.2-1 Indirect and Direct IW Operational Concepts

AFDD 5 focuses in particular on counterinformation and *information assurance* as components of a comprehensive operational view of IW. In this document, counterinformation is very close to the idea of indirect IW just mentioned—see and compare Figure 1.2-2 with Figure 1.2-1—and information assurance comprises both the enhancement and the protection of friendly information. In this view, the specific notion of the analog of direct IW, or offensive Netwar-type activity is shown within the category called *information attack* (see below). However, the details and notions of offensive IW, given its rather sensitive nature, have to date been the least-discussed component of a total picture of IW (at least in the open literature). In what follows, we focus on the materials from *AFDD 5* and its emphasis on counterinformation but it should be understood that there is a rapidly-growing body of material addressing the subject of IW and its many dimensions, and that there are evolving and occasionally conflicting viewpoints on the various aspects of IW.

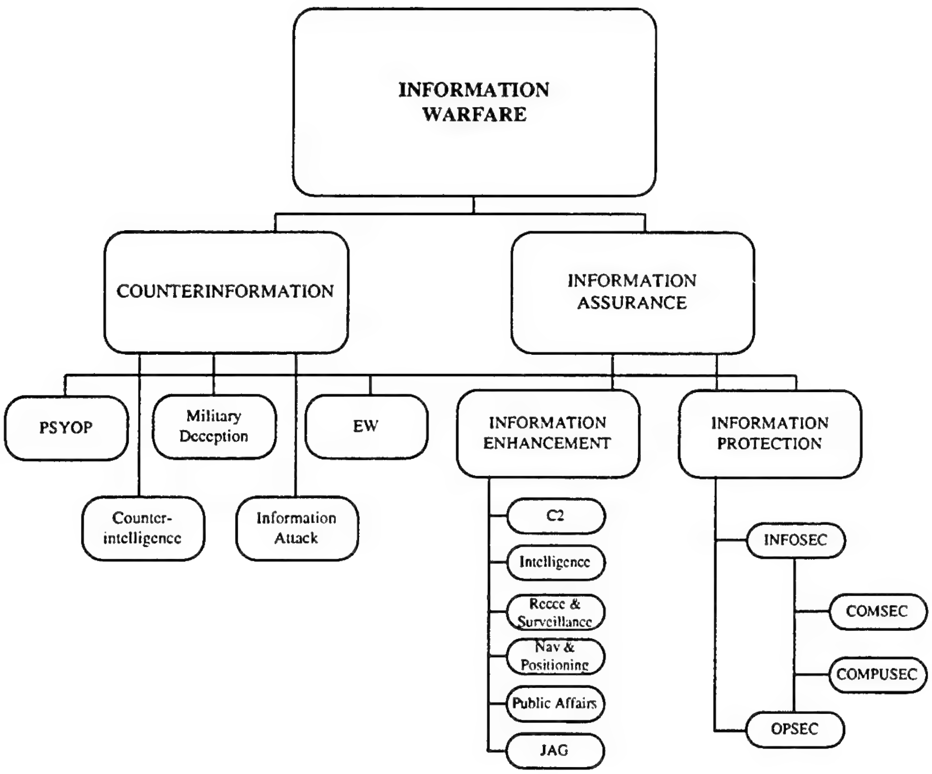


Figure 1.2-2 Prominent Information Warfare Activities

1.2.1 Counterinformation

Counterinformation activities establish information control and enable all other activities (recall our comments that what is called "counterinformation" in *AFDD 5* is very close to what is called C2W in *JCS MOP 30*). Combined with counterair and counterspace, counterinformation creates an environment where friendly forces can conduct operations with some degree of freedom of action, while simultaneously denying the adversary the ability to conduct those operations against friendly forces. Counterinformation seeks to establish a desired

degree of information superiority by destroying or neutralizing enemy information functions. The focus of the effort is on countering the enemy's ability to attain information dominance through information disruption, distortion, and denial. Disrupting vital information lines can confuse an enemy's ability to understand what is happening until it is too late to take appropriate or effective action. Distorting the adversary's understanding by inserting erroneous information into their system can create a false picture, forcing an opponent to act in accordance with friendly objectives. Denying information can create large gaps in an opponent's picture of a situation. All of these measures can confuse, delay, or inhibit enemy offensive actions and reduce reaction time for critical defensive measures.

1.2.1.1 Counterinformation Operations: Several Air Force operations strive to deny, exploit, corrupt, or destroy an adversary's information and its functions. Some of the activities that can operate on human and technical information systems include psychological operations (PSYOP), military deception, electronic warfare (EW), information attack, and counterintelligence (CI); these are briefly described below. (Note that these activities later form the framework within which we assess the effects of Offensive IW attacks on friendly informational components.)

Psychological Operations

PSYOP are designed to convey selected information and indicators to foreign audiences to influence their emotions, motives, objective reasoning, and ultimately their behavior. The purpose of PSYOP is to induce or reinforce foreign attitudes and actions favorable to friendly objectives. Modern PSYOP are enhanced by our ability to communicate massive amounts of information to target audiences with the intent of influencing their perceptions and decision making processes. Examples of this information include promises, threats of force or retaliation, conditions of surrender, safe passage for deserters, or support to resistance groups. During Operation JUST CAUSE, ground units employed loudspeakers to drive a fugitive from justice out of his hiding location and cause the surrender of thousands of Panamanian Defense Force personnel. In similar situations, USAF assets can be employed to broadcast radio and loudspeaker messages which may influence a wider audience.

Military Deception

Military Deception seeks to mislead foreign decision makers, causing them to act in accordance with the originator's objectives. Deception strategies may support national policies, military service programs, or tactical operations. Measures are designed to distract from, or provide cover for, military operations. Military deception, in the form of a feint or fixed force, can confuse and dissipate enemy efforts to interfere with friendly forces. These measures require accurate intelligence on the adversary's cultural, political, and doctrinal perceptions. Planners then are able to exploit and manipulate those biases. For example, during World War II's Operation FORTITUDE NORTH, the Allies dropped two bombs in the Pas de Calais for each bomb dropped in Normandy, successfully misleading German defenders as to where the actual beach landings would occur.

Electronic Warfare

Electronic warfare is any military action involving the use of electromagnetic and/or directed energy to manipulate the electromagnetic spectrum or to attack an adversary. Electronic warfare can create an electronic sanctuary in which friendly aircraft may operate. This sanctuary can help enable strike and counterair aircraft to proceed to and from their targets and to fully exploit their weapons without undue interference from electronically directed enemy air defenses. During DESERT STORM, effective force packaging, which included self-protection, standoff, and escort jamming, received much of the credit for the Air Force's astonishingly low loss rate.

Information Attack

Information attack encompasses activities taken to manipulate or destroy an adversary's information without visibly changing the physical entity within which it resides. Penetration of an enemy's information system has great value in combat because it offers the ability to incapacitate an adversary while reducing exposure to friendly forces. By using nontraditional tools, conventional sorties can be saved for other targets. Manipulation of data bases or parameters of reporting systems can cause incorrect information to distort leaders' decision making, or destroy the enemy's confidence in its information systems. An effective information attack could force an adversary to use less technical means because of friendly intrusion into the system. An example of information attack might be to interject into a radar data stream disinformation that causes the antiaircraft missiles to miss intended targets.

Counterintelligence

Counterintelligence consists of those information gathering activities (and resulting information gathered) that protect against foreign-sponsored espionage or terrorism. Counterintelligence threat estimates and vulnerability assessments identify friendly information weaknesses and vulnerabilities that may be exploited by an adversary. The importance of a strong CI capability is highlighted by the Cold War example of the Walker case. From the late 1960's to the 1980's, the US suspected the Soviets had foreknowledge of American naval exercises. However, it wasn't until the Walker espionage ring was exposed that the US discovered that the Soviets had been given naval cipher materials.

2. PROJECT OBJECTIVES

The objectives of this project were to:

1. develop a top-level model of a two-sided, aided adversarial decision making environment, and to decompose this model to a more specific level if possible

2. focus on representation aspects of the adversarial component of the model

3. conduct an assessment of informational vulnerabilities

4. examine the sensitivities of decision making quality to potential loss or degradation of information within the decision making process

As the task effort unfolded, it was realized that the first order of business was to collect information on each of a number of factors that bore on the development of the model. Aided adversarial decision making turns out to have a number of different dimensions, and there are a number of factors that influence the definition of a useful decision making model cast in an IW environment. Some of these raise issues that, to date, have not been very well researched at all—*e.g.*, human trust in automated/computer-based support (*i.e.*, decision aids) when the informational components in that aid are suspect to varying degrees. There has been work in the area of human trust in automation, but not specifically within this IW-type environment. Thus, the construction of a model which represents all the factors involved in aided adversarial decision making within an IW framework will likely require separate efforts to define decision making component processes heretofore unexamined. As we probed further, it was also realized that an overarching issue is that of informational value in the context of decision making. Notions of vulnerability of information and sensitivity of decision making to information corruption immediately require specification of notions of informational value in decision making. While this topic has been addressed (and we synopsize several prior works in this area herein), it is an area that, surprisingly, has not received as much attention as one might think. Here too, there are requirements and opportunities for new research in developing a comprehensive model of informational value and informational dependencies—in a quantitative sense—for decision making in an IW setting. Thus, we have not accomplished all these objectives, but believe we have made good progress toward them in the sense of establishing an understanding of several of the factors which will bear on the definition of a credible model of the type sought here. We do have a top-level model, we have addressed vulnerabilities and sensitivities, but have neither expanded on the model nor focused on adversarial representation as yet, due to the effort to better understand the roles of various contributing factors.

3. A TOP-LEVEL CONCEPTUAL DECISION MAKING MODEL

3.1 An Aided Decision Making Model

This study proposes a model of how experienced personnel make tactical decisions in complex command and control (C2) environments. The tactical decision making environment often involves time pressure, high risk, and uncertainty. Command and control is exercised based on the results of a set of tactical decisions. Theoreticians generally point out, command and control is not a collection of sensors, processor, displays, and data links. Rather, command and control is an extension of basic human decision processes by means of procedures, organization, and equipment. That is, sensors, automatic data processors, and communications equipment and systems are extensions of the decision maker's ability to gather, process, and disseminate information.

3.1.1 Possible Models and Model Components

Realizing the key to a better designed C2 system is a better understanding of the human decision making process, Wohl (1981) proposes a tactical decision process model called the SHOR paradigm, addressing the four generic decision making stages: Stimulus (data), Hypothesis (perception alternatives), Option (response alternatives), and Response (action). Basically, the SHOR paradigm is an extension of the stimulus-response paradigm of classical behaviorist psychology that provides explicitly for dealing with the uncertainty of input information and the consequences of actions. The SHOR paradigm does provide a good foundation for modeling human decision making and, in fact, those four stages can be further integrated and modified with more inside views. In the first half of the SHOR paradigm, the stimulus-hypothesis stages can be viewed as situation awareness (SA). That is, the decision maker is gathering information from the environment and trying to understand the state of the world as a basis for subsequent decision making. As a matter of fact, while considering decision making in complex and dynamic environments, the decision maker's SA is a crucial construct. Endsley (1995), in a special issue of *Human Factors* devoted to the topic, proposes a theoretical SA model based on a fairly complete literature review of the issues relating to SA.

The characteristics of tactical decision making map closely to those included in an area of research that has been labeled naturalistic decision making (Orasanu & Connolly, 1993). Research on naturalistic decision making seeks to develop descriptive models of how people, usually experts, make decisions about the dynamic, unstructured problems encountered in real-world settings. The recognition-primed decision (RPD) model (Klein, 1993) depicts how experienced people make decisions in natural settings. The RPD model emphasizes situational dynamics as one of the key drivers in selecting a course of action. The RPD model describes how decision makers can rely on experience to recognize situations and to identify viable courses of action, without comparing the relative benefits or liabilities of multiple courses of action. A more complex version of the RPD model, concerning "feature matching" and "story building,"

was proposed in a study by Kaempf, Klein, Thordsen, and Wolf (1996). This model also enlightens the modeling toward tactical-aided decision making. Furthermore, Cohen, Freeman and Wolf (1996) describe and discuss a framework for decision making, called the recognition/metacognition (R/M) model, that explains how decision makers handle uncertainty and novelty while exploiting their experience in real-world domains. This literature provides great guidance for personnel training also.

The Mixed-Initiative Model (MIM) proposed by Riley (1989) emphasizes the information flow between a machine, an operator, and the environment and serves as the basis for a dynamic simulation of human-machine interaction. This model offers a detailed representation of the interaction and information flow among the decision maker, the decision aid, and the world. There are four elements identified in this model: 1) decision aid system input, 2) decision aid system output, 3) human input, and 4) human output. The world node provides information to both the decision aid and the human decision maker and receives changes by the command and control by the human decision maker. This model provides good guidance for constructing a detailed information processing model for aided decision making.

Characteristic of each of the models discussed is the explicit recognition of the human tendency to structure the decision making situation to reduce cognitive complexity and, hence, reduce the information processing load.

To combine the model elements described above into a single model suitable for IW C2 activities, we propose a two-level, aided decision model. The model presented consists of 1) the Two-Sided Adversarial General Model, and 2) the Aided Human Decision Making Model. The Two-Sided Adversarial General Model is the upper level model and describes the relationship between two adversarial forces, both of whom have decision aids. The Aided Human Decision Making Model, based on the concept of the SA model by Endsley (1995), and also integrating the concepts from the modified RPD model by Kaempf et al. (1996) and MIM by Riley (1989), focuses on the detailed information processing in the human-decision aid cooperative system of either side of the adversarial forces in the general model.

3.1.2 Assumptions and Constraints

The proposed aided decision making model is based on the following assumptions and constraints:

- The decision making tasks discussed in this study are primarily focused on tactical, rather than operational, decision making.
- The decision environment is assumed to be adversarial, complex, time-pressured, risky, dynamic, and to contain elements of uncertainty.
- The decision making is facilitated by a data-fusion-based decision aid. The decision maker's information is primarily provided by the display interfaces of the decision aid.
- The decision maker is assumed to be experienced and well-trained, both in performing the designated C2 tasks and in using the decision-aiding system.

- A single decision maker is assumed. That is, neither group nor distributed aided decision making are considered in this study.

3.1.3 Two-Sided Adversarial General Model

This general model, as shown in Figure 3.1.3-1, depicts the information flow between the two opposing forces—adversarial and friendly. For each side, three major nodes are addressed: the human commander (the decision maker), the DF system (the decision aid), and the world/battlefield (the information resource). As shown in the diagram, in order for the decision maker to perform command and control for the battlefield, the sensors pick up (from the battlefield or the world) data involving states of the environment, adversarial forces, and friendly forces, and feed it into the decision-aiding system. The processed information is displayed to the human commander, who then can use it to make a decision. Besides current battlefield information, supporting information may also be accessed through those available databases connected to the decision-aiding system. The decision maker gathers information primarily by interacting with the display and control interface provided by the decision-aiding system. However, the decision maker also may collect information through other, unofficial sources. Once the information is gathered, the decision maker forms a situation model and, based on the model, plans the C2 actions.

Although the decision making paradigms in this model are generally the same for both sides, the information flow and the decision making results can be very different. The differences in characteristics inside entities are the determinants for different decision making results. It also implies that the information dependencies and vulnerabilities in aided adversarial decision making are determined by the entity characteristics in this model. Technology is a major factor—especially the ability to design and use sophisticated data sensors, data processing systems, interactive interfaces, and communications systems for C2. Cultural differences are another potential factor. Different cultures can produce differences in command and control patterns and in personal decision making processes, and therefore, require differently designed decision aids for maximum effectiveness. The influences on decision making by these factors will be discussed later in more detail.

3.1.4 Aided Human Decision Making Model

As shown in Figure 3.1.4-1, this model depicts a rather detailed view of the human decision making process. The basic relationships among human decision maker, decision aid, and battlefield have already been defined in the general model in the previous section. The human decision making process can be categorized into two major phases: situation awareness and action planning. That is, once the information is gathered from the decision aid and/or from the world, the decision maker forms a situation model and, based on the model, plans the C2 actions. This part of the model will be discussed following in more detail.

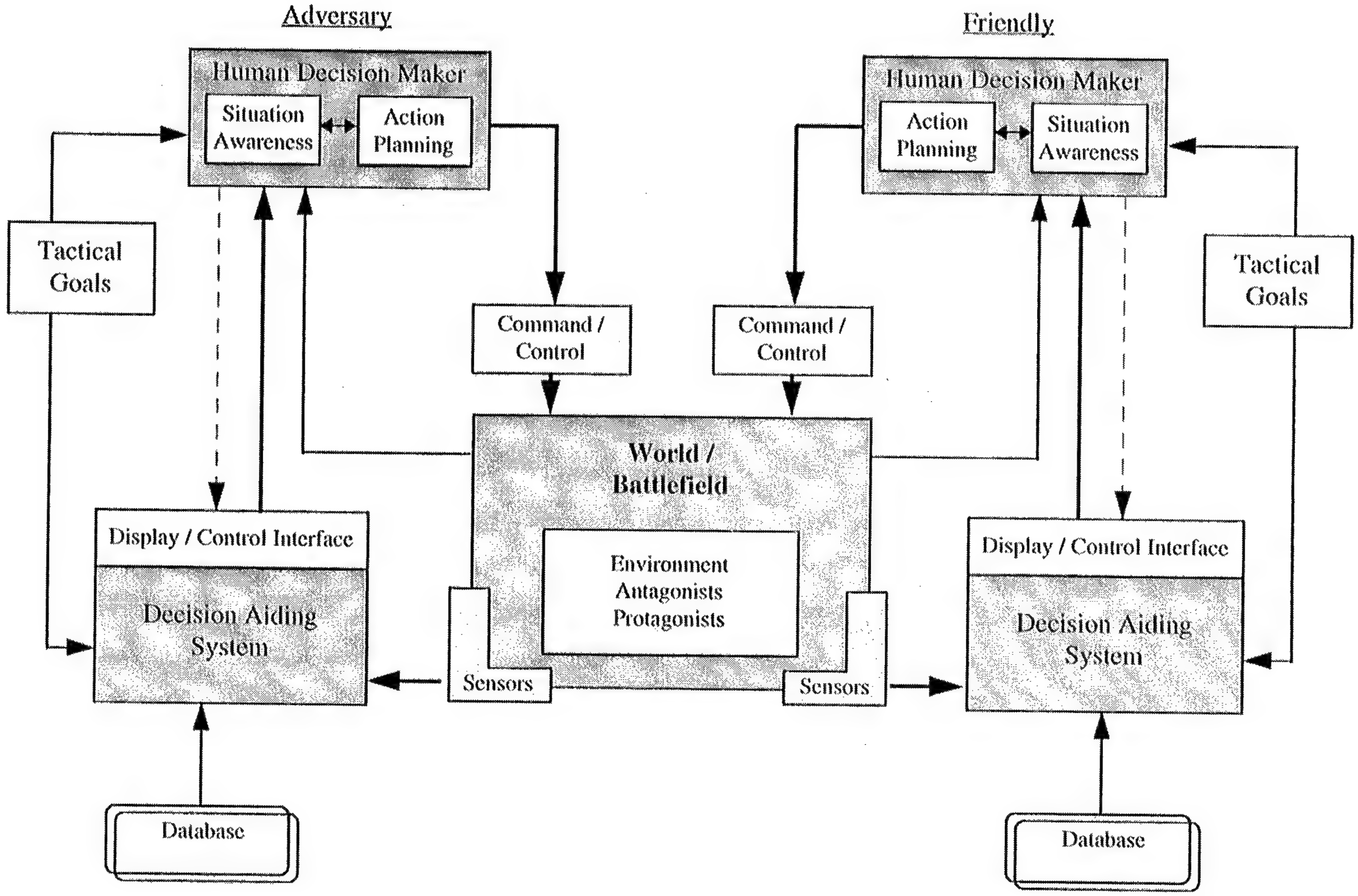


Figure 3.1.3-1 Two-Sided General Model

3.1.4.1 Situation Awareness: A theoretical model of situation awareness by Endsley (1995) provides a framework for the core of human and, hence, system decision making. That model includes three levels: perception of elements in the environment, comprehension of the current situation, and projection of future status. Based on the world model and the predictions of the future formed in the commander's mind, decisions are then made. In our Aided Human Decision Making Model,
Endsley's SA model is introduced and integrated as the main framework for the human decision making subsystem.

In the decision maker subsystem, the human commander gathers and perceives information about the environment through the display interfaces of the decision aid, and also obtains information through other sources. These can be classified as the first level of SA - perception of the elements in the environment. This is the stage which emphasizes data/information sampling in human decision making. The efficiency and effectiveness of information sampling are both very critical to SA at this level. That is, the sources of information (both in number and physical type), and the complexity of information are the factors "external" to efficiency and effectiveness. Determination of attention allocation is the typical way to assess performance during this stage.

There are two sources of information perceived by the human commander: one is from the displays of the decision aid (explicit communication) and the other is from the real world through other channels (implicit communication). Decision aids are designed to be the main channel for providing information. However, besides this "official" information, the human commander also receives information through "unofficial" sources, *e.g.*, watching or listening to the news or even talking to colleagues. The information perceived through those unofficial sources can sometimes be crucial and have great influence in aided decision making, for both good and ill.

By integrating the information from the decision aid and from other sources, the commander forms a holistic picture of the environment or world, *i.e.*, a world model. Inferring the system state based on the information perceived through the display interface, understanding the system, integrating the information from other sources, and then forming a mental model of the current world can all be categorized as the second SA level—comprehension of the current situation. That is, a mental model is created representing what is going on in the world of interest based on the information perceived from Level 1. In fact, this stage is the core of SA, since, (1) the third SA level, prediction, is solely based on the knowledge of the world model developed in this level, and (2) the first SA level, information sampling, is driven by the world model for better attention allocation.

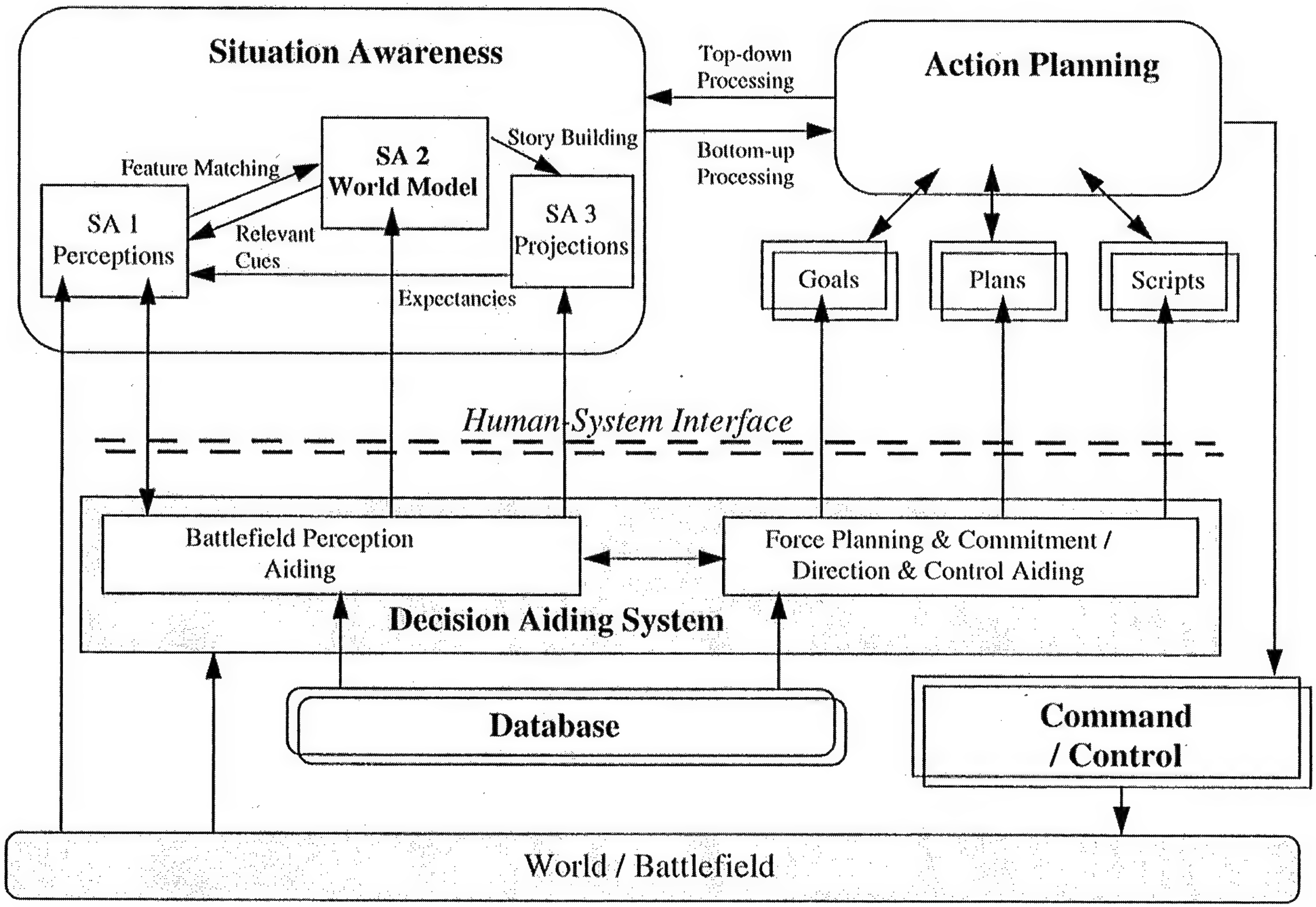


Figure 3.1.4-1 Aided Human Decision Making Model

In most of the decisions concerning SA and diagnosis the decision makers use "feature matching" and "story generation" strategies to build SA. As summarized by Kaempf et al. (1996), story building can be thought of as a mental simulation in which one constructs a story that explains how a state of events might have been caused. Often the decision maker observes seemingly disparate pieces of information that do not match any set of cues held in memory. There may not be enough information to trigger recognition of the situation, or the pieces of available information may appear to contradict one another. The decision maker must build a story that links the various pieces of observed information into a coherent explanation of the situation. On the other hand, if possible, the decision maker may go back to the first level of SA, *i.e.*, seeking more information to enhance and to modify the world model being built. More importantly, the information search is always based on building the model, even if it is still vague in the early stages. Story generation enables the decision maker to form certain expectancies and, based on these expectancies, to seek more information to confirm or modify the mental model. The continuous activities of filling in the information (or values) for the mental model, known as model-driven information sampling, is crucial to the quality of the resulting world model.

While forming a mental model of the world, the third level of SA is gradually elicited. Based on the forming world model, the commander predicts the behavior of the world. This provides the knowledge necessary to decide on the most favorable course of action to meet the specified goals. The projection of the future status of the world is always based on world model knowledge, and the conflicts and doubts generated during the prediction stage are the information used to refine or even revise the world model. Mental simulation appears once the diagnosis is made; the simulation also enables the decision maker to form expectancies of what should occur if the diagnosis is correct. These expectancies let the decision maker verify the accuracy of the diagnosis by prescribing what should be observed as the incident continues to evolve (Kaempf et al., 1996). In some cases decision makers use a mental simulation to project a given course of action into the future to determine whether it would work and, if not, whether it could be modified.

In fact, the border between Level 2 and Level 3 is rather vague. That is, the information exchange between world model development and future projection is highly interactive. Based on the world model formed mentally, the human commander utilizes that knowledge and predicts the possible future courses of the world to facilitate decisions for action.

3.1.4.2 Action Planning: Once the situation model is developed, the decision maker plans the actions for C2 based on the model. Upon the situation awareness, specific goals, the "ideal" future states of the world, are mentally formed for guiding the whole action planning. Plans of actions are then elicited for evaluating and modified. Related mental scripts, the predetermined action paradigms, can provide schema for action planning. Meanwhile, guided by the goals or plans formed, the human commander continuously modifies or refines previously formed predictions of world behavior and also the world model itself. This is so-called "top-down processing." In fact, a certain amount of backtracking of perception activities would also be expected.

In fact, some of the tactical decision makers' primary tasks are to determine which set of threats exist; the procedures will then tell them what actions to take. That is, the decision maker focuses on *whether* to engage in specific action, rather than *when* and *how* to engage, especially when the threats are ambiguous and proximal (Endsley & Smith, 1996). However, for other tactical decision making tasks, especially those of C2 oriented decision making, action planning is far more complicated than answering a "whether" or "go-no-go" question. This is why our model emphasizes the distinction between the action planning phase and the situation awareness phase.

3.1.4.3 Decision-Aiding: Considering the phases of human decision making defined in our model, decision-aiding functions can be further categorized into two classifications: battlefield perception-aiding and force C2-aiding, as shown in Figure 3.1.4-1. Battlefield perception-aiding basically assists the formation of a situation model. By processing and integrating the information from battlefield sensors, the decision aid can provide the human commander extensions for sensing and perception capabilities—that is, the decision aid can, at least, enhance the first level of SA. Some decision-aiding systems can reason further and match the information into certain pre-defined "situation models," and suggest or maintain a "good" mental situation model for the decision maker. Battlefield projection simulation, provided by an advanced decision aid system, can facilitate the mental situational projections of the decision maker. Action planning also can be aided by providing or facilitating the elicitation of action goals, action plans, and even action scripts based on the situation perceived. The main purpose of either the battlefield perception or the force C2-aiding functions is to reduce the mental workload, particularly in working memory load and in memory retrieval.

As implied by this model, the human commander does not usually just accept the information from the decision aids without inferring or judging. The human commander tends to process the information from the decision aids by inferring how the aiding system works. For example, when a human commander is warned by the computer that a hostile fighter is now flying from zone A toward zone B, he or she does not simply accept this piece of information. Instead, the human commander utilizes his or her knowledge of how the system works, *i.e.*, the system model, to refine or re-evaluate the information, assuming there is time. The knowledge of the system's functions, so-called "system" or "display" knowledge, comes into play while the system model is forming. By integrating the information from the decision aids and other sources, a world model is formed. That is, the human commander puts all the available information together, not necessarily with equal weight, and "understands" the world state, influenced by the system knowledge he or she possesses. Every commander potentially "understands" in his or her own mind in his or her own way.

3.2 Factors Influencing the Vulnerabilities of Aided Decision Making

According to Endsley (1995), several major factors influence the decision making process have to be interpreted through the SA mechanism. First, SA is a function of the system design in terms of the degree to which the system provides the needed information and in terms of the form in which it provides it. All system designs are not equal in their ability to convey needed information or in the degree to which they are compatible with basic human information-

processing abilities. Other features of the task environment, including workload, stress, and complexity, may also affect SA. Additionally, SA is a function of an individual's information-processing mechanisms, and as such, is influenced by innate abilities, experience, and training. The individual may possess certain preconceptions and goals that can act to filter and interpret the information about the environment and affect the formation of SA. The role of each of these factors in relation to SA, as well as the related implications of the vulnerabilities in aided decision making will be addressed.

3.2.1 System Factors

3.2.1.1 Situation vs. Action Information: The role of a well-designed decision aid is basically to improve the decision quality by providing processed and integrated information in an appropriate manner. The decision-aiding system is designed to help reduce cognitive workload, lessening demands on working memory and enhancing retrieval from long-term memory—therefore, reducing the time required for decision making and lowering the potential for error.

As noted in the model, battlefield perception and command and control planning are the two major types of information that can be provided by a data-fusion-based decision aid. In fact, the information dependency as well as the decision-aiding dependency may be different for battlefield perception-aiding and for C2 planning-aiding. For battlefield perception-aiding, the information dependency can be directly related to the decision maker's trust in the information provided by the aid. It is reasonable to postulate that the decision maker tends to depend on the aided information regarding higher SA levels if the trust is higher. On the other hand, for an experienced decision maker, the role of the action planning aid is rather a reminder or advisor. The aiding dependency may be relatively low if the actions for C2 are typical and well-defined, but when the content of C2 becomes more complicated, the information from the action planning aid becomes more important to the decision maker.

3.2.1.2 System and Interface Design: Both how well the sensors capture the data from the real world and how well the collected data is transferred and processed into useful information can influence the SA of the decision maker. Sensors with different functions and different locations act as the first information filter of the situation on the battlefield. Therefore, the sensitivity and the deployment of these sensors determine the first level of information loss. That is, the system may not acquire all of the needed information. The second level of information loss occurs in the DF processes. Well-designed DF systems can integrate data and provide more comprehensive information to the decision maker. However, data processing is always associated with information reduction. Not all of the information acquired by the system may be available to the operator. That is, the DF system itself is the second layer of information filter preceding the decision maker.

The third level of information loss is through the display interface which provides information to the decision maker. That is, there may be incomplete or inaccurate transmission to the human operator of the information displayed by the system and that directly acquirable from the environment. As Endsley (1995) points out, the way in which information is presented via the operator interface will greatly influence SA by determining how much information can be

acquired, how accurately it can be acquired, and to what degree it is compatible with the decision maker's SA needs. Since the major goal of decision aids is to provide "useful" information to assist operators to make "good" decisions, the DF system and its human interface must be carefully tailored to the needs of the user.

In fact, the decision maker's system knowledge or system model can greatly influence the information loss, too. As noted in the proposed model, the decision maker processes the information from the decision aid based on his or her mental system model. The system model can influence the information processing both positively and negatively. One positive influence might be that, by knowing the capabilities or data-processing characteristics of the decision-aiding system, the decision maker's system model can guide him or her to look beyond the displayed information and to compensate to the information loss or biases by the system. On the other hand, system knowledge can also act as another information filter; and important cues or information may be ignored or less-weighted for decision making processing.

3.2.1.3 Technology: Generally, advanced technology may directly relate to the capabilities of sensors and decision aid systems, giving better quality and quantity of information. Technology can help to develop sophisticated and advanced decision-aiding systems—hopefully to help, rather than to frustrate, the commander. On the other hand, as Taylor & Selcon (1994) pointed out, increasing difficulties with operator SA seem to be associated with the employment of advanced automation and display/control technology in increasingly complex systems and in highly dynamic environments. That is, possible problems associated with information overload to the decision maker may occur, degrading SA and, hence, the final decision quality. Therefore, technology can influence the decision quality in both positive and negative ways. Human-system interface design is the key to cope with technology-induced information vulnerabilities.

3.2.2 Task Factors

3.2.2.1 Task Complexity: Task complexity negatively affects both the decision maker's workload and SA through factors such as an increase in the number of system components, the degree of interaction between these components, and the dynamics or rate of change of the components. In addition, the complexity of the decision maker's tasks may increase through the number of goals, tasks, and decisions to be made regarding the system. According to Endsley (1995), a person's SA is restricted by limited attention and working memory capacity. Fortunately, long-term memory stores, most likely in the form of schemata and mental models, can largely circumvent these limits by providing for the integration and comprehension of information and the projection of future events. This complexity may be some what moderated by the degree to which the operator has a well-developed internal representation of the system to aid in directing attention, integrating data, and developing the higher levels of SA, as these mechanisms may be effective for coping with complexity. These very mental models, though, can be exploited by an adversary under suitable conditions.

3.2.2.2 Stress: Endsley (1995) provides a good review of recent literature on how stress factors affect SA and decision making. It seems that stress may affect SA through the decrements in working memory capacity and retrieval. For SA Level 1, cognitive tunnel vision

results—that is, the attention allocation in the perception of environment elements is rather narrow and focused, so that certain critical information may be neglected, which may lead to failure. SA Levels 2 and 3, both of which are highly dependent on the performance of working memory, may be greatly affected by stress in a negative way. Therefore, a biased and immature mental model may be generated due to the effect of poor working memory capacity in SA Level 2. This mental model may erroneously guide the attention for information sampling (SA Level 1), focusing on wrong pieces of information and hence biasing or weakening the mental model.

It can be expected that information overload (that is, too much information displayed or fed to the decision maker in a short period of time) would negatively affect the performance of decision making under stress. Thus, both insufficient and excessive information can degrade decision quality.

The keys to ensure a smaller drop in decision quality are to avoid information overload of the decision maker and to assure that a "good" mental model will be prompted. To diminish the likelihood of information overload, a decision aid with information integration or DF capability is essential to provide the amount of information the user needs. Display interface design is also critical. With any interface design, training, especially in simulation or scenario studies, helps to build certain metamodels *a priori*, so that a "correct" mental model may be prompted with less demand on working memory.

3.2.2.3 Uncertainty: Uncertainty has a major effect on the quality of decision making since generally humans are not truly "Bayesian" and are affected by various limitations and biases that prevent them from integrating information in an optimal fashion. Therefore, decision making biases or heuristics may induce more errors as the uncertainty increases. That is, the uncertainty associated with data could be critical to the quality of decision making, thus increasing its vulnerability. Moreover, information order effects (the order in which the information is presented to the decision maker) significantly affect probability estimates, identification judgments, and engagement decisions (see review by Adelman, Bresnick, Black, Marvin & Sak, 1996.)

While applying a quantitative decision model, it should be noted that if the human needs to process the information to select an action/decision, the quantitative model can only provide a normative or upper-bound of the performance under rather ideal assumptions. On the other hand, if the decision is made by automated components and suggested to the human commander for final evaluation, the way in which the information associated with the decision is presented will be critical to the final decision value or quality.

3.2.3 Individual Factors

3.2.3.1 Individual Differences in Information Processing: The ability to detect relevant information within a field of irrelevant information varies widely between individuals. It appears to be related to the decision makers' ability to cognitively restructure their perceptions so that the relevant is separated from its background. This cognitive restructuring has been found to be relatively robust across different senses, and is known as field independency. Field independent

individuals are more able to perform visual search tasks, find relevant cues while driving, and correctly locate the gravitational axis when their bodies are tilted. Although the aim of DF and interface design is to enhance the ratio of relevant-to-irrelevant information, many threats will be difficult to perceive, particularly in the early stages of threat development. A test for field dependence/independence could, thus, be valuable in enhancing overall system performance.

3.2.3.2 Trust and Confidence: The commander may have more or less confidence regarding the accuracy of information received, based on its perceived reliability or its source. That is, when using a decision aid as the major information source, the trustworthiness of the decision aid determines the degree of uncertainty associated with the information it provides, both while inferring the system model and later, in mapping to the mental model. Therefore, the confidence level associated with an information source may influence the decisions that are made using information from that source. As the literature emphasizes (Muir & Moray, 1989; Moray & Lee, 1990), operators' trust directly affects the use of the automatic system. This implies that the decision maker might refuse to use the integrated information provided by an advanced or automatic decision aid if he or she does not have a good and positive internal model of the decision aid. On the other hand, automation-induced complacency may induce decision failures based on over-trust (Singh, Molloy, & Parasuraman, 1993). Furthermore, Lee and Moray (1994) found both trust and self-confidence are factors to consider when determining the level of automation and the specific function allocation in semi-automatic systems. Therefore, the decision maker's subjective feelings of trust in the decision aid as well as his/her self-confidence can both affect the use of the integrated information provided by decision aid.

3.2.3.3 Experiences and Training: For making decisions in tactical environments, Amalberti & Deblon (1992) found that the expert pilots tended to have better "metaknowledge" for optimizing planning, and were able to restrict consideration to more likely eventualities. Even though the flight plan was never executed as planned, these pilots had solved a large set of potential problems in advance, which simplified the decision process when deviations were necessary under operational time pressure. A large portion of in-flight decision making, then, becomes focused on collecting enough information to confirm with confidence that the pilot's internal picture of the situation is accurate (Amalberti & Deblon 1992). In this scenario, the preflight mission plan forms a set of expectancies that direct the search for information and interpretation of that information (Endsley 1995). Based on this understanding of the situation, pilots will attempt to project likely future occurrences, allowing them to prepare responses in advance or to take actions to avoid such events. This strategy acts to minimize the load associated with in-flight responses to the unexpected, which may often be accompanied by stress and short decision times. Avoiding the need to make on-the-spot decisions in stressful situations through anticipation and advanced response development can be seen as an effective strategy for coping with the demands of this environment.

3.3 A Final Remark

It must be emphasized that who is friendly and who is adversarial is in the eye of the beholder. Thus, many, if not all, of the remarks made from the perspective of one or the other of the two sides might be considered to be applicable to either. While it may be expected that the

two sides in a two-sided case do not perfectly mirror each other in either decision making behavior or in influences, the various parameters and discriminants which generally influence decision making may be interpreted to be applicable to either participant

4. INFORMATION DEPENDENCIES IN AUTOMATED DATA FUSION PROCESSING

4.1 Introduction and Overview

As noted in Sections 1 and 2, this project deals with *aided* adversarial decision making. The legacy of research in computer-based decision aids is extensive, and for several years there were conferences which focused on and discussed the work being done by a rather large community in the development of not only prototype aids themselves but also on the underlying principles of decision aid development. In the present case, we hypothesize that the general nature of a computer-based decision aid for each adversary in our general model takes the form of, and is based on, the notion that a data or information fusion process provides the basis for the aid. Data fusion (DF) processing is itself a rather broad and multidisciplinary topic but can be modeled, to about the same level of fidelity as our general model in Section 3, by a "process model" originally developed by the Joint Directors of Laboratories Data Fusion Group (JDL/DFG), a defense laboratory DF technology oversight committee. This general model is shown in Figure 4.1-1 below, and can be seen to comprise 4 "Levels" of processing:

- Level 1: those processes involved with normalizing a set of multisource-based inputs (a data preparation step prior to combining/fusing), association-correlation-assignment processing (to relate observations to hypothetical objects and related estimation processes), and fusion-based estimation processes which estimate both the kinematics and identity of the targets hypothesized. Thus, Level 1 processing produces what might be called a "labeled set"—of individual targets (points in space), each having kinematic and identity labels.

- Level 2: those processes involved with situational estimation, traditionally involving aggregation of single (Level 1) object estimates into *order of battle* (*OB*) structures, and behaviorally-based estimates (events and activities). Thus, Level 2 processing, largely but not exclusively symbolically-based, produces, by fusing Level 1 estimates, *a priori* knowledge, and other observations, a contextual interpretation of an abstraction typically labeled a "situation."

- Level 3: those processes, also predominantly symbolic in nature, that produce what is in essence a special situation estimate traditionally called a "threat" estimate. A threat state or situation is distinguished from benign situations by three factors: the idea that a lethal capability exists on the hostile side, that there is an opportunity to employ that lethality, and that there is an intent to use that lethality. Hence, Level 3 processes focus on estimating these factors in particular.

- Level 4: those processes which enable a sense of "intelligent control" or adaptation to the overall process. Typically these processes are considered to involve either or

both control over input source/sensor operations (sometimes called “sensor management” or “collection management”), and intelligent adaptation of the internal (Levels 1–3) processes of the DF processing itself, e.g., parametrically or even by controlled switching and optimization in the use of multiple algorithms or processes for a given DF function.

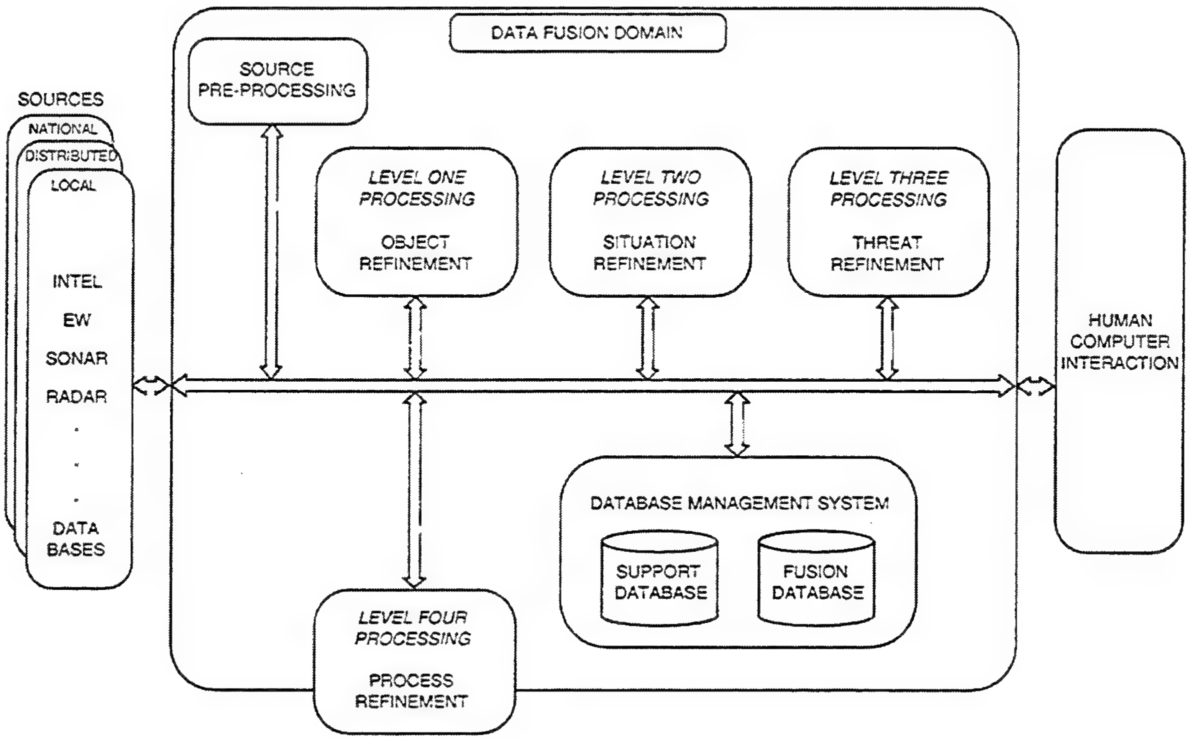


Figure 4.1-1 JDL/DFG Data Fusion Process Model

4.2 Information Dependencies in Data Fusion-based Decision Aids

As a contribution to beginning to get a sense of information dependencies in the overall aided adversarial decision making model, in this section we attempt to characterize the information that each of these four Levels of DF processing depend on. It is difficult (and actually beyond the scope of the current task) to do this to a high degree of fidelity but this section will characterize the nature of the information that these processes rely on. DF processing, as might be guessed, depends on the specific details of a particular application and on the domain of application, but a general view can, indeed, be put together. In what follows, we characterize these dependencies according to each DF Level.

4.2.1 Level 1 DF Processing

4.2.1.1 Alignment Processing Operations: The Alignment function is that in which dynamic data from multiple sources is "normalized" in a variety of ways necessary to condition it or prepare it for later fusion-related processes. Informational dependencies in these processes are shown following:

Table 4.2.1.1-1 Alignment Function Informational Dependencies

Alignment of:	Purpose(s)	Process(es)	Information Dependencies
Multisource locations (*i.e.*, location of input sources)	Co-register source locations	Coordinate transformations	Source site locations
	Bias removal	Bias estimation	Source specific bias factors Choice of reference source
Intersource timing differences	Normalize time as required in subsequent estimation processes	Interpolation, extrapolation of source-specific measurement to "reference time" Time-propagate pseudo-measurements to reference time, as per source models in estimation routines	Intersource timing differences and choice of reference time; (coarse) models of target-measurement processes to support interpolation/ extrapolation Intersource timing differences and choice of reference time; (fine) models of target-measurement processes to support estimation-based projections
Image-image, image-terrain registration	Co-register objects-to-objects, objects-to-terrain	Correlation techniques	Sample data on reference targets or reference points
Coordinate systems	Normalize all estimates to a common coordinate reference system	Coordinate transforms	Specific data and knowledge of individual coordinate systems employed
Unit systems	Normalize all estimates to common units	Unit transforms	Specific data and unit systems employed

4.2.1.2 Association and Correlation Processing: At any given "node" in a DF processing "tree," *i.e.*, a generic DF processing architecture, there are three important and generalized steps that lead to a solution of the combinatoric optimization problem usually referred to as "association" or "correlation." This fusion subprocess is the framework about which some type of optimal "assignment" of the many observables coming from the multiple sources is determined, whereby the observables can be thought of as being assigned to a set of estimation processes which are generating improved—*i.e.*, fusion-based (*i.e.*, based on exploiting

these multiple measurements)—estimates of parameters and states of interest in the problem domain. The three subprocesses are: hypothesis generation, hypothesis evaluation, and hypothesis selection ("Hg, He, Hs"). This idea is depicted below in Figure 4.2.1.2-1:

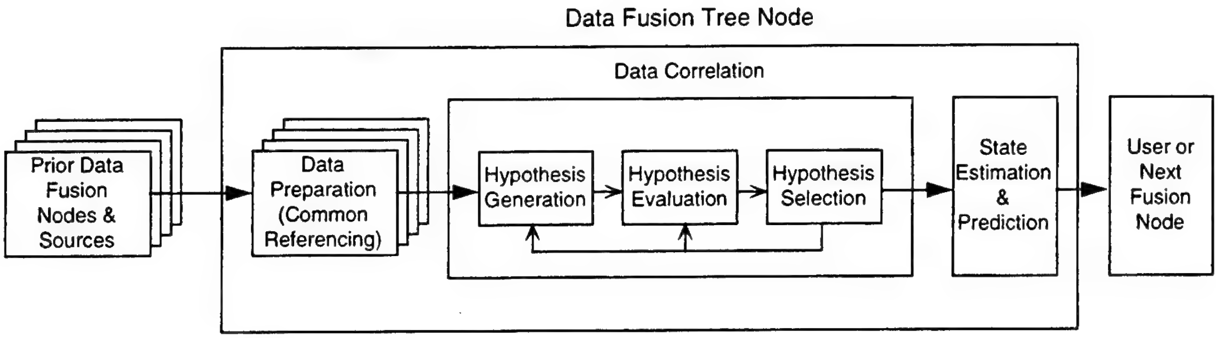


Figure 4.2.1.2-1 Typical Data Correlation Processing Steps Within a DF Node

Each of these subprocesses and their information dependencies are depicted in Table 4.2.1.2-1.

Table 4.2.1.2-1 Data Correlation Processing Steps and Information Dependencies

ASSOCIATION/ CORRELATION SUB PROCESS	PURPOSE	TYPICAL, REPRESENTATIVE METHODS	INFORMATION DEPENDENCIES
Hypothesis Generation (Hg)	To identify all feasible hypotheses that could explain data	Pattern recognition, gating, templating, knowledge-based	Extensive dependencies on target characteristics and behavior, target density, etc.–see Table 4.2.1.2-2
Hypothesis Evaluation (He)	To score the "likelihood" of any nominated hypothesis from the Hg process	Ad hoc, probabilistic, possibilistic, logical/symbolic, NN, random set theory	Strongly dependent on degree of knowledge of *a priori* statistics and "uncertainty in the uncertainty"–*i.e.*, second order statistics
Hypothesis Selection (Hs)	To set up and solve the assignment problem for ultimately deciding on the specific assignment of measurements	Mathematical programming methods of various description	Inputs here are scored hypothesis alternatives resulting from Hg and He processes; dependence on problem domain information is lessened by these pre-filtering operations

It can be seen that by and large the information dependencies of these processes are primarily in the Hg subprocess which requires reliable problem domain information so that the nominated set of hypotheses is inclusive of the true hypotheses; this is the fundamental

requirement for good Hg process performance. The details of these dependencies are shown in Table 4.2.1.2-2 on the following page.

As results get handed off from subprocess-to-subprocess, there is decreasing direct dependence on "world state" type information but there are implicit effects on the performance of the He and Hs processes in that these processes are designed in conjunction with Hg, and the expected outputs from Hg. That is, the overall process design is a coupled one. Consequently, any uncertainty in the expected type of domain problem and its characteristics and information, *i.e.*, in an *a priori* sense, will lead to either uncertainties or unnecessary complexity in the association-correlation process, since *all possible* hypotheses will need to be nominated if there is a lack of, or uncertainty in, possible behaviors in adversarial operations.

Modern-day approaches to DF processing are beginning to incorporate dynamically adaptive processing, *i.e.*, incorporating Level 4 processing (many legacy DF systems were and are open-loop, without adaptive aspects). These processes then require *real-time* world state information as inputs to whatever "control laws" for adaptation are embodied in the overall process.

PROBLEM CHARACTERISTICS	No. of Scans			Hypotheses		Assignment Uniqueness		Evaluation Metric						Gating Strategy			
Hypothesis Generation Design Alternatives	Single Scan (N=1)	Multiple Scan (N=n)	Batch (N=∞)	Single Hypotheses	Multiple Hypotheses	Unique Assignment	Non-Unique	Geographic Distance	Generalized Distance	Mahalanobis	Probabilistic	Ad hoc	Location Only	Kinematic	Target Attributes	Target Identity
Nature of Input Data																
• Locational Data		Y	Y	Y	Y		Y	Y	Y	Y	Y	Y	Y	Y		
• Attribute Parameters		Y	Y	Y	Y		Y	N	Y	Y	Y	Y			Y	
• Target Identity		Y	Y	Y	Y		Y	N	Y	N		Y			Y	Y
• Observation Rate (high)	Y	Y	Y	Y			Y									
Target Characteristics																
• Location Predictability		Y	Y	Y	Y		Y	Y		Y	Y			Y		
• Identity Attributes		Y	Y	Y	Y		Y			Y	Y	Y			Y	Y
• Maneuverable	N	Y	Y	N	Y		Y									
Target Density																
• High Density	N	Y	Y	N	Y		Y					Y				
• Low Density	Y	Y	Y	Y	N		N									
Sensor Characteristics																
• High False Alarm Probabilities (PFs)	N	Y	Y	N	Y		Y				Y					
• Known Observation Statistics		Y	Y	Y	Y		Y			Y	Y					
• Complex Signal Propagation	N	Y	Y	N	Y	Y	Y									
• Low Positional Resolution		Y	Y		Y	N	Y					Y	Y			
Available Processing/ Decision Time Frame																
• High Processing/Long Timeframe		Y	Y		Y	Y	Y			Y	Y					
• Low Processing/Short Timeframe	Y	N	N	Y	N	Y	Y	Y	Y		N	Y				

Table 4.2.1.2-2 Hg Process Design Alternatives: Dependencies on Domain Problem Characteristics

4.2.1.3 Object Position and Identity Estimation: Level 1 processes culminate with estimates of object position (and kinematics for moving objects) and identity based on the assigned measurements for the multisource inputs. Techniques for estimation of the kinematic characteristics of targets have traditionally been dominated by the "Kalman Filter" (KF) approaches, involving various flavors of discrete time, recursive state estimation methods. The approaches to the estimation of target identification (sometimes called *classification*) have historically been dominated by feature-based methods from pattern recognition science but of late have trended toward the use of model-based approaches.

The information dependencies in these processes can be characterized as shown in Table 4.2.1.3-1.

Table 4.2.1.3-1 Level 1 Processes and Information Dependencies

Sub-process	Purpose	Representative Methods	Informational Dependencies
Target Position and Kinematic Estimation	Same	Kalman Filtering, neural network methods, fuzzy logic+Kalman Filtering	Assigned observations, source observational model assumptions, assumed target dynamic behavior (model), source/observation sampling rate, removal of biases
Target Identity Estimation	Same	Methods of pattern recognition, especially feature-based methods, and model-based approaches	Assigned observations, statistical assumptions, various models in model-based approaches

One of the major vulnerabilities of the position and kinematic estimation algorithms is their inability to remove systematic biases. Such biases, thus, form one important focal point in KF design and in DF process design. Efforts are made to both understand and limit these biases to the extent possible, primarily so that they induce effects that are less than would be expected from maneuvering targets—that is, such that bias effects do not inadvertently cause the tracking system to believe that the target has maneuvered, in which case so-called "maneuver gates" are employed that, if incorrectly instantiated, can lead to corruption and loss of track. This degradation may occur if the target density is relatively high (closely-spaced targets), in which case large amounts of confounding observations may enter the association gate for the given track, raising the possibility of incorrect association. Hence, if an IW attack were made on the internal processing operations of the DF decision aid, in particular inducing false biases into the system, possibly severe degradations in performance could result; this is one part of the DF process that definitely should be protected. Additionally, most KF's, as for any algorithm, involve various "models" and assumptions in their formulation. Errors in those models regarding their representativeness of true/actual target behaviors will also, naturally, lead to performance degradation. Sensitivities of such behaviors have not been systematically studied in the DF community but clearly some loss in performance would occur in such cases. So another area to protect in the internal processing is that which contains the model structure and assumptions in the KF structures (*e.g.*, sensor noise characteristics, process noise characteristics, etc.). The basic idea here is to protect the integrity of the designed-in models of the KF processing.

In a somewhat similar sense, the target identification (ID)-estimating techniques used in DF processes are dependent on assumptions and modeling techniques and details. This is especially true for the so-called "model-based" approaches employed for the automatic target recognizer (ATR). Additionally, since many existing/legacy DF systems rely on kinematic/position-based approaches to data association, any corruption achieved by a hostile in degrading the association/correlation processing would also propagate errors—*i.e.*, misuse of erroneous features and other observable ID-related characteristics—into the fusion-based ID estimating processes. Biases again are a point of vulnerability in ID processing. Further, there are known (but not necessarily fully quantified) influences of misregistration for different approaches to DF processing for ID in the cases involving 2D imagery-type data: the usual DF approaches involve pixel-fusion, feature-fusion, and decision-fusion; in the order just cited, these methods are decreasingly dependent on accurate co-registration of the data sets being fused. However, if an adversary knows that pixel-based ID fusion techniques are being employed, these can be defeated by insertion of false biases that would corrupt the data association and the consequent performance of pixel-based methods.

4.2.1.4 Dependencies of Level 1 DF Processes on Data Base Information: The models, assumptions, and other necessary *a priori* (and dynamic) information upon which Level 1 DF processes depend are often stored in computer-based data bases of some type and structure. Table 4.2.1.4-1, drawn from (Waltz & Llinas, 1990), shows some of the categories of data bases required by Level 1 DF processing. Structured analyses of these data would reveal yet other detailed dependencies and vulnerabilities that hostile IW operations could attack.

Table 4.2.1.4-1 Categories of Data Bases Required by Level 1 Data Fusion

Data Base	*Typical Contents of Data Base*	*Uses of Data*
Target Attribute Data Base	Target-feature relationships; classification data (parametric or nonparametric), rules, networks, frames, or templates	Sensor preprocessing for target classification by attributes
Target *a priori* Data	*A priori* quantities of targets by class, predicted target locations and trajectories, orders of battle	Prior data used in Bayesian classifiers Prior target locations used for sensor management
Target (Track) Data Base	Typical data for each target: Target (track) index Current state estimate Statistics of state estimates (*e.g.*, $x, \dot{x}, y, \dot{y}$) covariance matrix of errors) Track state (initiate, confirm, loss) Time of initiation, last update Level 1 ID (friend-foe-neutral) Level 2 ID (target type) Level 3 ID (target class) Confidence data, each ID (*e.g.*, measure of uncertainty in ID) Sources of identity (sensors, contributions and reports) Target priority for sensor management	Data association, tracking, and attribute combination processes maintain this data base for sequential processing Multiple hypothesis association and identification algorithms may also maintain candidate hypotheses in this data base, or in a separate (relational) data base This data base forms the input to levels 2 and 3 fusion processing Related fire control, weapon guidance, and sensor-management data may also be included
Track History	Chronological sequence of sensor reports and association, classification decisions (same data as above)	Used for batch association and attribute processing in which stored time periods are processed at one time
Sensor Model Data	Range, line-of-sight (LOS), detection-ID performance data against various target types, in varying environments	Used by sensor manager to predict the performance of sensors against targets for assignment

4.2.2 Level 2 and 3 DF Processing

Determination of the current situation (an abstract and inherently imprecise term needing detailed specification for automated systems, *e.g.*, DF processes) or threat state is a key function of military command, control, communications, computers, intelligence, surveillance and reconnaissance (C4ISR) systems and processes. It is generally agreed by decision theorists that dynamic decision making is in fact characterized by its dependence on situational estimation. We have implied such dependencies in the models described in Section 3. To amplify this point, we also show here, in Figure 4.2.2-1, another model of a dynamic decision making process (taken from Reidelhuber, 1984), which shows some of the interdependencies of C2 functions and decision-processing, along with the role of situation assessment; note too the "Markovian" or state-transition dynamic nature of the decision making and situational assessment processes reflected in this model.

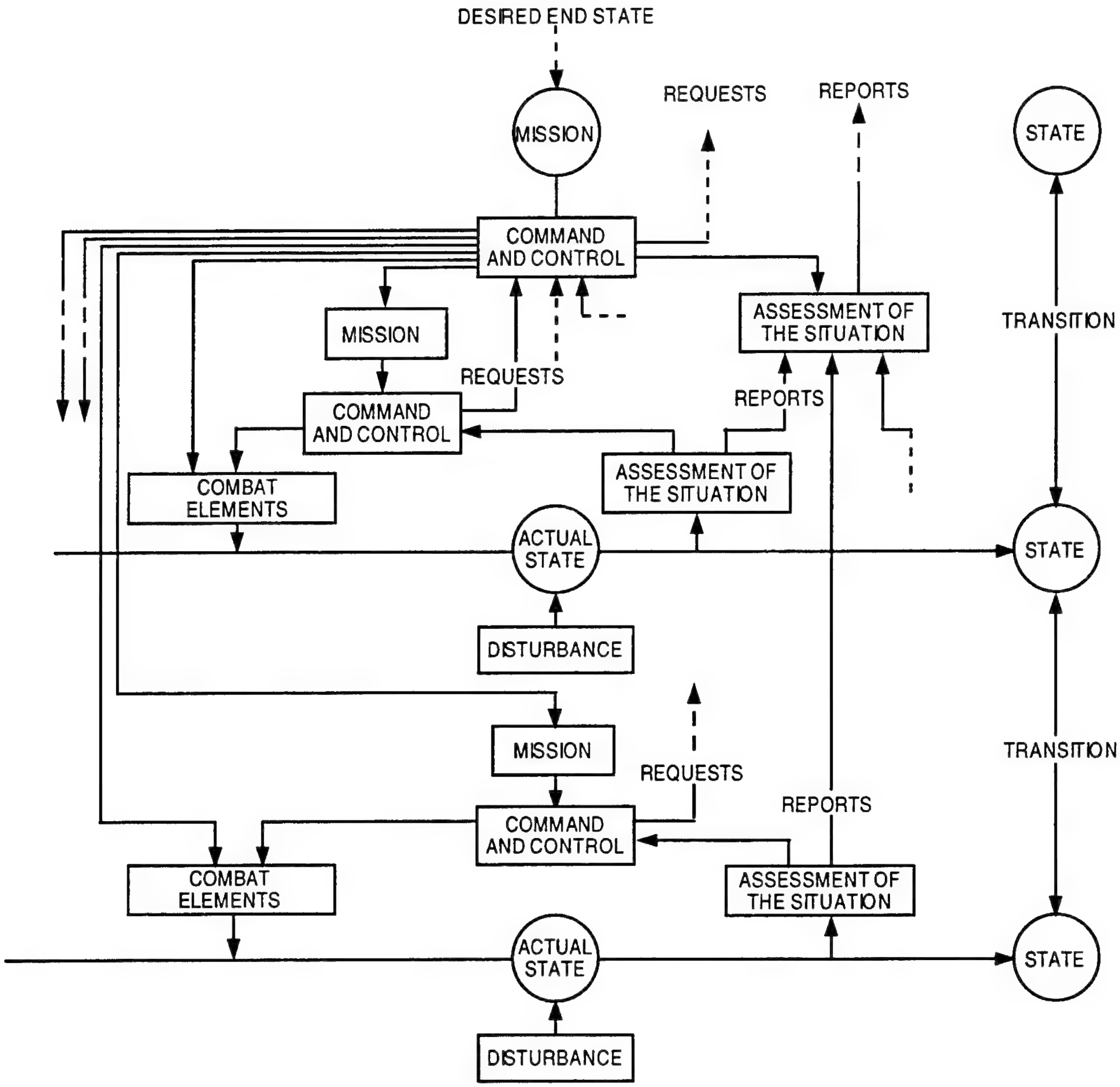


Figure 4.2.2-1 Dynamic Decision Making and the Role of Situational Assessment (After Reidelhuber, 1984)

The automated estimation of these situational or threat states through DF processing generally involves symbolic or knowledge-based techniques through which knowledge is encoded in software and applied to the dynamic data flowing into a DF-based decision aid. Level 2 and 3 DF processes attempt to generate a contextual interpretation about the Level 1 data, augmented by whatever *a priori* knowledge can be applied. The DF processes are the result of pattern-matching type operations in the software which compare the current realtime dynamic data to the *a priori* knowledge bases, generating whatever inferences that process yields. Hence, the DF processes are embedded in the knowledge itself, and are not "prescriptive" in the sense of the mathematical equations, etc., typically employed for Level 1 DF operations. In some sense, this knowledge is also a "model"—an "expectation model" for target behaviors and

interrelationships based on whatever foreknowledge is available. In this same sense the Level 2 and 3 processes depend on and are vulnerable to the specific characteristics of this knowledge.

Knowledge-based systems (KBS) are vulnerable to such IW operations as deception because of various weaknesses in the knowledge base (*e.g.*, see Table 4.2.2-1 below), although the perpetrator must not be so clever as to prevent the KBS from producing its inferences, *i.e.*, the hoped-for false inferences. That is, the KBS should be deceived, not jammed. Table 4.2.2-2 shows some of the operational aspects of KBS deception that would equally apply to the deception-based IW attack on a DF-based decision aid.

Table 4.2.2-1 Deceiving Knowledge-Based Systems

Weaknesses in the Knowledge Base
Reliance on the Past (Insensitive to Innovative Behavior)
Belief in What has Been Seen (Failure to Cross-Validate)
Basis in Doctrine
Treating the Unexpected as Anomalies (Not as Clues)
Over-Generalization of Inferences (As Causal [Observed Maintenance Routines = Required Maintenance])
Weaknesses in KB Development (*e.g.*, Failure to Check Consistency)
Lack of Self-Understanding re Boundaries of Knowledge

Table 4.2.2-2 Deceiving Knowledge-Based Systems: Operational Aspects

• **A KBS is Deceived if:** • The System Creates its Products (computationally feasible response) • The Product Contains Errors Which: • Derive from Intentional Deceptive Actions • Give the Deceiver an Advantage
• **Deception Attacks Data/Sources through Collection Processes Directly**
• **Deception Attacks Other Components Indirectly**
• **Weaknesses in the Data/Sources Derive From** • Weakness in Collection/Exploitation • Weaknesses in Data Plausibility Models

KBS systems, as their name implies, depend on knowledge bases. To assemble an inference about the complex data/information structure we call a "situation" typically requires an extensive body of knowledge, depending on how sophisticated the DF decision aid is designed to be. Generally, situation and threat estimation is about determining relationships, *e.g.*, as those shown in Table 4.2.2-3 (from Waltz & Llinas, 1990), which require fairly broad knowledge to achieve.

Table 4.2.2-3 Categories of Data/Knowledge Bases Required by Level 2 and 3 Data Fusion

<table>
<tr><th>Data Base</th><th>Typical Contents of Data Base</th><th>Uses of Data</th></tr>
<tr><td>Behavioral Data Base</td><td>Target and event behaviors and characteristics; temporal-spatial templates, tactics, combat doctrine, et cetera</td><td>Used for target and aggregated target set identification, situation assessment. Also used for sensor management to predict sensor view opportunities</td></tr>
<tr><td>Terrain Features</td><td>Topology, hydrology, road-rail networks, cultural features, obstacles, locations of cover and concealment, et cetera</td><td>Used for identification of individual targets by behavior and for aggregation of targets
Sensor management uses for LOS prediction</td></tr>
<tr><td>Airway Doctrine</td><td>Corridors, restricted zones, routes and schedules (flight plans)</td><td>Used to identify targets by planned behavior</td></tr>
<tr><td>Own-Forces Status</td><td>Disposition of forces, strength and condition, reserves, logistics, C2, planned course of action</td><td rowspan="2">Both situation assessment and threat refinement functions use this data to determine course of action hypotheses and the effects on sensor management, and DF performance</td></tr>
<tr><td>Intelligence on Enemy Forces</td><td>Disposition of forces, strength and condition, reserves, logistics, C2, probable intent, targets of interest and course of action</td></tr>
<tr><td>Threat Capabilities</td><td>Sensor and weapons performance capabilities:
Performance envelopes
Detection, warning, track, ID capabilities
Countermeasure vulnerability</td><td>Assess threat capability against own forces, predict threat behavior; sensor manager predicts enemy detection of own emissions to reduce exploitation</td></tr>
<tr><td>Situation Data Base</td><td>Location of all entities, relationships and predicted courses of action; identification of potential threats and opportunities for all forces</td><td rowspan="2">Maintains the current hypotheses of threat situation assessment; dynamic data base is sequentially updated as assessments are updated by completion of Level 2 assessment</td></tr>
<tr><td>Threat Data Base</td><td>Assessment of threatening entities, events, and activities; estimate of own-force vulnerability (sensors and weapons) based on enemy opportunities, means, motives from Level 2</td></tr>
</table>

Since much of the content of such knowledge bases is established from peacetime intelligence, hostiles can corrupt the construction of them by deceptive operations during military exercises, etc. Additionally, these knowledge bases are also vulnerable to possible Direct IW attack since they are part of the internal DF processing operations.

4.2.3 Level 4 DF Processing

Level 4 processing, in essence, involves the execution of "control laws" that enable dynamic adaptation of the DF processing, typically in two senses: (1) by dynamic alteration of the data/sensing/input processing, and (2) by dynamic adaptation of the internal DF processes themselves. Whether or not type (1) control can be done or not in part depends on whether the DF process has authority over the data collection and sensing type operations; this is not always the case but can often be enabled in tightly-coupled, "organic" type systems or platforms. This

type of control, typically called sensor management or collection management in the DF community, can be effective in thwarting deception, in that deceivers typically depend on observing the targets' sensing systems as a means of verifying that the deception has created the intended effect (an important part of deception operations, influencing the deceivers sense of risk of action). Hence, intelligent Level 4 DF techniques that exploit any *a priori* knowledge regarding expected hostile deception operations can provide a means for counter-deception. Type (2) control depends on knowing the sensitivities of whatever "quality metrics" are being used in the control process to adaptations in other parameters or processes in the fusion operations. Typically such sensitivities must be determined heuristically or empirically since not many inter-relationships in DF processes can be determined from first principles or closed-form expressions. Once again, such expressions would be "models" in the DF system, and again, possibly vulnerable to Direct IW attack.

5. MODELS OF THE ROLE OF INFORMATION DEPENDENCIES IN DECISION MAKING

Central to the analysis of the effects of IW on decision making is the assessment of Informational Value in decision making. IW attacks will lead to the deletion, corruption, and alteration of quanta of data and/or information in any automated decision making support system or in the mind of the user/analyst/operator. Following the assertions of the Defense Information Systems Agency (DISA) which argues that perfect protection of information in networks is impossible or at least unaffordable into the mid-term future, information will indeed be compromised and systems should be designed under this assumption. So the immediate question is, if this happens, "So what?" There are various answers to this question that can be derived from various viewpoints—*e.g.*, we discuss human trust in automated systems in Section 7 where the reader will see that such trust is compromised and not easily re-established if automated decision making support systems yield false or misleading output—but here we focus on the notions of the value of information in decision making in general, particularly with a quantitative approach.

The approaches taken here draw heavily from the works of Morris, Yovits, and Ackoff, among others (see References), each of whom has examined the question of informational value in decision making in somewhat different but related ways. The models and concepts drawn from these references will be seen to also have similarities to those from the theories associated with Reinforcement Learning, which also constructs a probabilistic (expectation-centered) model of the roles of information in learning processes.

5.1 One Probabilistic Framework

It will be seen that the models constructed herein (we emphasize that they are drawn from the cited works) can be argued not to attack the value of information in decision making directly but indirectly, in the sense of the reduction in uncertainty of choice in the decision maker's options for a "course of action" that related information produces, *i.e.*, in deciding on a preferred—and correct—option among those possible or feasible. So it will be seen that the structure of a decision model relates action or decision options (courses of action) to the consequent outcomes in a probabilistic framework. In these models, it is also important to understand that the use of a conditional probability-type approach implies that both the human or computer-based decision maker and the true relationship between decision-choices and outcomes can all be modeled probabilistically. Thus, when probabilities are described below, it must be distinguished as to whether they are those assigned by a human, a computer program, or by "nature" in the sense of characterizing actual worldly behaviors.

5.1.1 On the Semiotic Nature of Informational Types

Much of what follows in this section is excerpted from Yovits and Abilock (1974). Morris (1964) points out that it is now generally recognized that "information theory" is not a

rival to, or a substitute for, a general theory of signs (*i.e.*, semiotics). The frequently-cited Shannon and Weaver (1949) information theoretic viewpoint concerns the transmission of a message as a symbol string independent of its content. Y. Bar-Hillel (1955) and D. M. MacKay (1952) take alternative views. MacKay regards information as that which changes our representations, *i.e.*, our signs. Gaining information is, thus, changing our expectations, *i.e.*, our dispositions to respond, caused by a sign. He distinguished between *selective* and *semantic* information. Selective information gives the information necessary to select the message itself and is not concerned with the content of the message; it is in some sense a signaling theory. Semantic information on the other hand is concerned with the content of the message. Shannon's theory, thus, deals with selective information problems. Among other authors, Carnap and Bar-Hillel (1952) and Winograd (1972) are perhaps best known for their work in the area of semantic information.

The aforementioned views of information are two of the three approaches or levels identified in studies of information theory by Weaver. The third level is known as the *behavioral or effectiveness level* and deals with the effect that information has on the person using it. Ackoff (1958) has dealt with information problems at this behavioral level. The work of this project is considered to lie in this area, since we are concerned with the effect of information on *decision making behavior* by a human, in a computer-assisted mode.

5.1.2 Developing a Decision Model Which Reflects Informational Value

Morris (1964) has identified three general requirements of action involved in the decision making process. A decision maker must: (1) obtain information about the situation in which he is to act, (2) he must select among courses of action, and (3) he must execute this alternative by some specific course of behavior. To effect a meaningful analysis of information, one must examine in detail that which makes decision making such a challenging activity: uncertainty. We concern ourselves with uncertainty because we will argue that a key role for information is its influence on uncertainty within a decision making process. After careful examination of decision models described in the literature, Morris concluded that these existing models do not provide a comprehensive representation of the uncertainty that exists in decision making. Most of the models are concerned solely with decision makers who have an advanced state of knowledge about the decision situation in question. The information science aspects of decision theory must, however, cover comprehensively not only those decision makers who are expert, but also those decision makers who are average or rather poor. It is extremely important in developing a formal role for information science that all levels of effectiveness of decision makers be considered. For this purpose, a very general decision model is proposed.

A *decision model* consists of a number of decision elements, including a set of courses of action, a set of possible outcomes, a goal or set of goals, a function relating outcomes to goal attainment, and a set of states of nature.

The decision maker usually views a complex decision situation in terms of his roles and responsibilities within it, for selecting courses of action (COA), which then lead to possible outcomes. He may be uncertain about what outcomes will occur when a particular course of action is executed. This uncertainty associated with the execution of the alternatives is what

Yovits, Foulk, and Rose (1981) call *executional* uncertainty. A second type of uncertainty identified is *goal uncertainty*. The decision maker may have only a vague notion of the goals to which he aspires, and he may also be uncertain as to the degree to which each of the outcomes will satisfy the various goals. The third type of uncertainty which the decision maker confronts is that concerned with the states of nature. He may not be able to identify all the possible states, but even if he could, he may still be uncertain as to the relationship between the set of states and the other decision elements. This is termed *environmental uncertainty*. A complete model of a complex decision situation must deal explicitly with all of these types of uncertainty. The conceptual decision model suggested by Yovits and Abilock explicitly recognizes all of the decision elements as well as the associated sources of uncertainty. The following Table 5.1.2-1 summarizes these ideas and uncertainty types:

Table 5.1.2-1 Developing a Decision Model Which Reflects Informational Value

TYPE OF UNCERTAINTY	ASPECT REPRESENTED
Executional	Outcome Probability, given a selected COA
Goal	Goal Uncertainty (specifically), and/or relationship between Outcomes and Goal Satisfaction
Environmental	State-of-Nature Uncertainty (specifically), and/or relationship between States of Nature and other Decision Elements

5.1.3 Mathematical Aspects of the Model

Again, the following represents an excerption from Yovits' works in both Yovits and Abilock (1974) and Yovits, Foulk, and Rose (1981) in particular, with some paraphrasing. A decision maker makes a sequence of related choices from among a discrete set of alternatives

$$A = \{a_1 \cdots a_m\}$$

The number of elements m in this set may not be constant over time since there may be uncertainty with regard to these elements. The execution of a particular course of action results in the occurrence of one of a set of possible outcomes

$$O = \{O_1 \cdots O_n\}$$

The number n may also vary over time. *Executional* uncertainty, *i.e.*, uncertainty as to the relationship between a particular course of action a^i and an outcome o_j will be denoted by the subjective probability estimate w_{ij}, the likelihood that the execution of course of action a^i will result in outcome o_j. The set of relevant States of Nature ("situations") will be denoted by

$$S = \{S_1 \cdots S_r\}$$

where r may also vary over time according to the decision maker's current understanding of the decision situation. The probabilities of occurrence of these (environmental uncertainty) states will be denoted by the subjective estimates

$$P(S_1)\cdots P(S_k)\cdots\cdot P(S_r)$$

The values assigned to the decision outcomes that reflect the relative value of each outcome with respect to goal attainment will be denoted by $v(O_j)$[1].

The decision elements A, O, $v(O_j)$ are dependent upon the state of the external environment. For example, courses of action which seem reasonable under one set of conditions may be wrong under other circumstances. These dependencies can be incorporated in the model by defining the sets A and O to reflect the decision maker's current understanding of the courses of action and the outcomes for each of the states of nature. Also, a set of w_{ij}^k and $v_k(O_j)$ can be identified for each state of nature. Figure 5.1.3-1 depicts this suggested mathematical representation for a particular state of nature Sk. More details can be found in (Yovits & Abilock, 1974) and (Yovits et al., 1981).

Relative Values							
Outcomes		$v_k(o_1)$	$v_k(o_2)$	...	$v_k(o_j)$	...	$v_k(o_n)$
Courses of Action		o_1	o_2	...	o_j	...	o_n
	a_1	$w^k{}_{11}$	$w^k{}_{12}$	...	$w^k{}_{1j}$	...	$w^k{}_{1n}$
	a_2	$w^k{}_{21}$	$w^k{}_{22}$	...	$w^k{}_{2j}$	...	$w^k{}_{2n}$
	.	.	.	...	.	...	.
	.	.	.	...	.	...	.
	.	.	.	...	.	...	.
	a_i	$w^k{}_{i1}$	$w^k{}_{12}$	...	$w^k{}_{ij}$	...	$w^k{}_{in}$
	.	.	.	...	.	...	.
	.	.	.	...	.	...	.
	.	.	.	...	.	...	.
	a_m	$w^k{}_{m1}$	$w^k{}_{m2}$	...	$w^k{}_{mj}$	...	$w^k{}_{mn}$

Figure 5.1.3-1 The Decision Matrix for the *k*th State of Nature

[1] Note that there can be several versions of such values as mentioned previously, i.e., those (imperfectly) assigned by the human user, the human programmer of the decision aid, or by Nature, the true value associated with the real outcomes.

We have modified this model to show, diagrammatically, the additional possible States of Nature and the notion that this process evolves in time as well. This is considered important because it is the States of Nature that are considered to be estimated by the Data Fusion (DF) process-based decision aid for the decision maker (DM) as "situational estimates" in the "Level 2" element of the DF model. We hope to augment Yovits' decision model with this component later. This modified diagram is shown below:

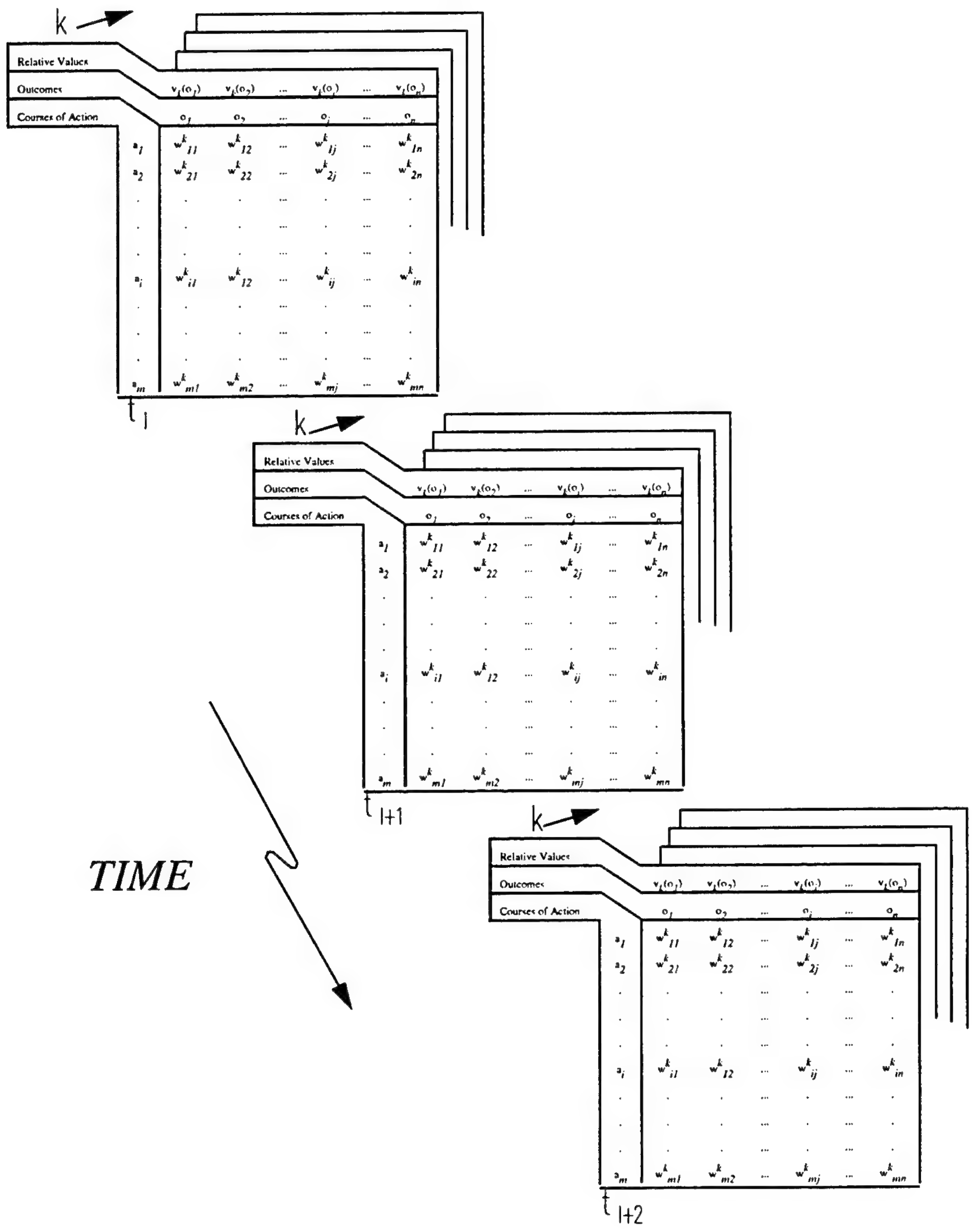


Figure 5.1.3-2 Modified Decision Matrix Showing Possible States of Nature as a Function of Time

Yovits' mathematical decision model consists of this (single-state) decision matrix together with some decision criteria which, when applied to the decision matrix, results in the selection of probabilities of courses of action. The actual decision rule that is used is dependent on the decision maker's own attitude toward uncertainty. For example, if the decision maker is conservative, he may select that course of action which maximizes his minimum possible gain. There are many different criteria which can be used, but in this analysis Yovits assumes that the decision maker assigns probabilities to the alternatives which are proportional to their *relative expected value*. The decision rule that recommended is as follows, and a number of interesting results follow from this rule. The expected value, *EV,* is defined by

$$EV(a^i) = \sum_{k=1}^{r} P(S^k) \sum_{j=1}^{n} w_{ij}^k \, v^k (Oj) \qquad [1]$$

That is, the expected value of each alternative is the sum of all the possible values weighted by their probabilities of occurrence.

This generalized decision model provides a framework for a formal and comprehensive representation of uncertainty in decision making. *As such, it importantly provides a suitable framework for examining the role of information in decision making that is also formal and comprehensive.*

The *effect of information* is to change the decision maker's representation of the various types of uncertainty. His decision model at time t + 1 will be a revised version of his model at time t. The way in which a particular decision maker utilizes information to revise his representation of the various types of uncertainty is highly individualistic. The generalized decision model permits the application of a large number of possible *learning* [2] rules.

5.1.4 Developing a Quantitative Measure of Informational Value and Quantity

Although the separate effects of the various types of uncertainty are clearly important, they are only of significance in their combined effect on the decision maker's understanding of the situation. The amount or value of the information contained in a data set can be meaningfully expressed only in terms of the total effect of the data on the decision maker's model of the decision situation.

Regardless of what decision rule a decision maker is utilizing, it is possible to obtain a distribution that reflects the decision maker's overall inclination toward the various courses of action. Yovits assumes, as already suggested, that the decision maker chooses a course of action with a probability proportional to its relative expected value. Thus, $P(a^i)$ is defined by

[2] The effects of Learning are considered quite important to the development of this model but will not be addressed in depth herein due to limits on the overall effort; recall our remarks on the similarities of the DM models reported on here and those used in modeling Reinforcement Learning processes – we expect to study these RL models in the next phase.

$$P\,(a^i) = \frac{EV\,(a^i)}{\sum_{i=1}^{m} EV\,(a^i)} \qquad [2]$$

where EV(a^i) is given by Equation (1).

The "Yovits" decision matrix representation shown in Figure 5.1.3-1 defines the decision situation in the context presented. It explicitly relates courses of action to: (1) observable outcomes; (2) values of these various outcomes to the decision maker; and (3) the states of nature. *This matrix, thus, may be defined to be the decision state of the decision maker.* This decision state is a complete description of all of the elements which enter into any decision making situation. The uncertainty in this decision state can be measured and calculated, and this will be indicated later. The *impact of information* on reducing the uncertainty in this state function may then serve as a measure of information. Since the information can also be related directly to the values of the various outcomes, it is therefore also possible to calculate directly the *value* as well as the *amount* of the information (in the context of impact to outcomes).

Equation (1) provides the relationship which yields the Expected Value *(EV)* of any course of action a^i. The uncertainty which exists for any decision state will be a function of the mean square variance of the expected values of the various courses of action. For example, if all the *EV's* are the same, the decision maker will be totally uncertain as to which alternative to choose and the variance will be zero. If the decision maker is completely certain as to his course of action, then all of the *EV's will* be zero but one which will be finite. For such a situation, the variance can be shown to be a maximum.

The mean square variance, σ^2, is defined as

$$\sigma^2 = \left[\sum_{i=1}^{m}\left[EV(a^i) - \mu\right]^2\right] \Big/ m \qquad [3]$$

and the mean, μ, is defined as

$$\mu = \left[\sum_{i=1}^{m} EV(a^i)\right] \Big/ m \qquad [4]$$

where m is the number of possible courses of action.

Yovits now defines the *value of the decision state* as the summation of the expected values of all the possible courses of action weighted by the probability of each course of action. In symbolic terms,

$$V\ (DS) = \sum_{i=1}^{m} P(a^i)\ E(a^i) \qquad [5]$$

The information contained in a decision state is related to the mean square variance of the expected values of the courses of action. To be precise, the information is related not to σ^2 but rather to σ^2/μ^2, since information should be measured by relating it to the variance measured in units of the mean; this measure is somewhat analogous to the coefficient of variation. This must be the case since a given variance of *EV's* will clearly be much less significant when the mean of the *EV's* is large than when the mean is small. The quantity σ^2/μ^2, from Equations (3) and (5), is:

$$\sigma^2/\mu^2 = \frac{V(DS)}{\mu} - 1 \qquad [6]$$

It is perhaps more meaningful to view this relationship in terms of the $P(a^i)$'s. With the use of Equations (2), (4), and (5), one obtains

$$\sigma^2/\mu^2 = m\sum_{i=1}^{m} \left[P\ (a^i)\right]^2 - 1 \qquad [7]$$

This quantity possesses the desired properties for an information measure. The more uncertain the decision maker is, the less the amount of information in his decision state. Thus, Yovits defines this fundamental quantity to be the amount of information in a particular decision state.

That is,

$$I = m \sum_{i=1}^{m} \left[P(a^i)\right]^2 - 1 \qquad [8]$$

Note that this quantity has a minimum of zero when all the $P(a^i)$'s are equal to 1/m. This is complete uncertainty. The quantity has a maximum of (m - 1) in the case of complete certainty where one of the $P(a^i)$'s is one and the others are zero.

When there are only two possible courses of action, the quantity I will assume values from zero to one. It will be equal to one under conditions of certainty, *i.e.*, when the probability of choosing one course of action is one and the other probability is zero. Accordingly, Yovits defines the unit of information in terms of a deterministic two-choice situation. This unit is called a *"binary choice unit," or b.c.u.*

When there are m possible courses of action, then the maximum amount of information from Equation (8) is seen to be (m - 1) b.c.u.'s. This is in agreement with a well-known principle that a minimum of *(m-1)* choices from pairs of alternatives is required when there are *m* alternatives to consider. This is pointed out in (Ackoff, 1958). More explicitly, if (m-1) choices are required and the maximum amount of information in each choice is one, then the maximum amount of information is (m-1). Analogously, the minimum amount of information is zero.

In summary, Equations (6) and (8) provide a method of obtaining the value of information in addition to the amount.

We can now define a quantity called the "index of determinism."

$$D = \sum_{i=1}^{m} \left[P(a^i)\right]^2 - \frac{1}{m} \qquad [9]$$

Note that this is just I/m. This quantity assumes the value zero when all the $P(a^i)$'s are equal (the case of total uncertainty) and the value (1-1/m) when the situation is completely deterministic. For large m, it will approach unity. Thus, the index of determinism is a quantity varying from zero to one which measures the determinism of the decision state.

5.1.5 Properties of the Information Measure

The suggested information measure possesses a number of desirable properties. It is defined in terms of a fundamental unit of measure which we termed the binary choice unit, or b.c.u. The consideration of additional but highly unlikely courses of action has a very small effect on the amount of information in the decision state.

Another desirable property of the information measure is "sequential additivity." The amount of information in a decision state can be measured all at once or the process can be broken up into several steps with the consideration of a few alternatives at a time. Regardless of which method is used, the amount of information in the entire decision state is the same.

A measure of the amount of information in a data set or message can be arrived at by computing the difference in the amount of information in the decision state before and after receipt of the data. That is, the amount of information is arrived at by considering the impact this new data has on the decision maker's decision state. In symbolic terms, I(D), the amount of information in data set D, is

$$I(D) = I_{t+1} - I_t \qquad [10]$$

where I_{t+1} and I_t are the amounts of information in the decision state after and before receipt of the data set.

It should be noted that the amount of information in a data set may be either positive or negative. In general, positive information sharpens or refines the decision maker's understanding of the situation in that it either reduces the number of structural components in the model or reduces the dispersion in one or more of the various probability distributions in the model. Negative information, on the other hand, either increases the number of structural components (*e.g.*, the addition to the model of a previously unknown alternative or outcome) or increases the dispersion in the various distributions. Negative information, despite a possible connotation of the term, does represent information that is of significance to the decision maker.

5.1.6 Discussion and Summary

A formal measure for the amount and the value of information contained in a data set or message has been suggested. It quantifies information in terms of its effect on the state of the decision maker, where a decision state is defined so that it represents a complete description of the decision maker's overall level of understanding about a particular decision situation at a particular point in time. This measure is universally applicable for pragmatic information. This is equivalent to Weaver's level three which is concerned with the effects of the message upon the recipient.

In order to evaluate this measure of information, it is convenient to use a generalized information system model. The use of this model then permits the evaluation of the measure of information in terms of the reduction of uncertainty. This evaluation could be made in terms of any kind of a decision rule. Yovits has suggested a reasonable decision rule that can be used, and developed relationships based on this rule. Virtually any other decision rule could be used for evaluating the effects of the various uncertainties referred to. It would also be possible to evaluate the decision state of the decision maker in a purely descriptive sense.

In summary, the proposed information measure by Yovits et al. is a function of the effect that a set of data has on a decision maker's decision state. This decision state is defined in such a way that it reflects the decision maker's understanding of a particular decision situation at a particular point in time. Hence, I is a situation dependent and time dependent measure. Clearly it must be time and situation dependent since the same data will have different significance to different decision makers at any point in time or to the same decision maker at different times.

5.1.7 Further Remarks on the Yovits Model I : Temporal Dynamics and Relational Information

Here, using Whittemore and Yovits (1973), we expand on some of the details of the model structure discussed above.

5.1.7.1 Temporal Dynamics: We have, following Yovits, said that a decision maker is required to make a sequence of related choices from among a discrete set of alternatives $A = \{a^1, a^2, ..., a^m\}$. Since the DM may be uncertain about the nature and number of elements in this set, m is not, in the long run, a fixed and/or known constant. The execution of a particular course of action results in the occurrence of one of a set of possible outcomes $O = \{o_1, o_2, ... o_n\}$. To allow

for unexpected outcomes, n too must be interpreted as variable over time. The DM may be uncertain as to the relationship between a particular course of action a^i and an outcome o_j. The likelihood that the execution of course of action a^i will result in outcome o_j can be denoted by the subjective probabilistic estimate w_{ij}.

After a DM has determined his overall goal structure, he must then assign numbers (in terms of value units) to the various decision outcomes that reflect the relative value of these outcomes with respect to goal attainment. These relative values can be denoted by $\{v(o_j)\}$.

The set of relevant states of nature can be denoted by $S = \{s^1, s^2,...,s^r\}$. As with m and n, r must also be interpreted as a number whose value may vary according to the DM's current understanding of the decision situation. The probabilities of occurrence for the various states of nature can be denoted by the subjective estimates $P(s^1), P(s^2),...,P(s^r)$.

The general interpretation of m, n, and r as variables suggests obvious problems with respect to the probabilities wij and P(sk). Recall, however, that these values depend on the DM's current understanding of the situation. In general, this understanding changes over time; nevertheless, at any one point in time at which the DM is required to use his decision model to make a decision, m, n, and r assume whatever values reflect his current understanding of the situation. Hence, at any particular point in time,

$$\sum_{j=1}^{n} w^{ij} = 1 \textit{ for } i = 1, 2, ..., m \textit{ and } \sum_{k=1}^{r} P(s^k) = 1.$$

The decision elements A, O, $\{w_{ij}\}$, and $\{v(o_j)\}$ are dependent upon the state of the external environment. Courses of action which seem quite reasonable under one set of conditions may be totally nonviable under other circumstances; similarly, a decision outcome which is very possible in one state may be quite impossible in another state. Also it is clear that (a) the probability with which a particular course of action results in a particular outcome and (b) the value of a particular decision outcome, are both dependent upon the state of nature. These dependencies can be indicated as follows: the sets A and O can be defined so as to reflect the DM's current understanding of all possible courses of action and all possible decision outcomes respectively (*i.e.*, for all states of nature); also, a set of $\{w_{ijk}\}$ and $\{v^k(o_j)\}$ can be assumed to exist for each state of nature. For state of nature s^k, the suggested mathematical representation is depicted in Figure 5.1.3-1.

5.1.7.2 Relational Information: The generalized decision model discussed provides a framework for a formal and comprehensive representation of uncertainty in decision making. As such, it also then provides a suitable framework for examining the role of information in decision making in a way that is also formal and comprehensive. A plausible approach to analyzing information is to look separately at its impact on the various types of uncertainty.

The information contained in a set of data (either unexpected new data from the external environment or feedback data from past decisions) has either structural value or relational value or most likely both. If the data indicate to the DM that his understanding of the structural components of the decision situation is incomplete and/or incorrect, then these data contain structural information. For example, the occurrence of a previously unknown decision outcome or the discovery of a new, viable course of action are informative in that they enhance the DM's understanding of the structural components of the situation. Similarly, if the data cause the DM to reassess his overall goal structure (*e.g.*, perhaps he is being too conservative) or to recognize another relevant state of nature, then the data are structurally informative.

On the other hand, data that help the DM refine his model of the relationships that exist between known structural components contain *relational information*. For example, a refining of the DM's understanding of the states of nature probabilities or the probabilities that the execution of a course of action will result in the various outcomes occurs as a result of using relational information. Similarly, data that allow the DM to assess more accurately the relative values of outcomes according to a given goal structure are *relationally informative*.

In general then, the effect of the information is to change the DM's representation of the various types of uncertainty; his decision model at time t + 1 will be a revised version of his model at time t. Structural information either changes the overall goal structure or the nature and number of components in the sets A, O, or S. Given that the DM has resolved a certain amount of structural uncertainty, the effects of relational information are to change the probabilities associated with the execution of a course of action

$$[w_{ij}{}^{k}]_{t+1} = [w_{ij}{}^{k}]_{t} + \Delta w_{ij}{}^{k} \; ; \qquad [3]$$

the probabilities associated with the state of nature

$$[P(s^{k})]_{t+1} = [P(s^{k})]_{t} + \Delta P(s^{k}) \; ; \qquad [4]$$

and/or the relative values of outcomes

$$[v^{k}(o_{j})]_{t+1} = [v^{k}(o_{j})]_{t} + \Delta\, v^{k}(o_{j}). \qquad [5]$$

The way in which a particular DM actually utilizes information to revise his representation of the various types of uncertainty is highly individualistic. The generalized decision model is amenable to the application of a number of possible *learning rules*. Whether a DM will actually use any of these formal learning rules is somewhat doubtful. Hence, explicit enumeration of possible learning rules and a detailed discussion of their application would not add anything to the discussion at this point. It is important to note, however, that the generalized decision model provides a framework in which the DM can apply whatever learning rules he desires.

5.1.8 Further Remarks on the Yovits Model II: DM Effectiveness, Effectiveness of Information, and External Information

Recall we have said that there are DM-assigned and Nature-assigned (*i.e.*, true or actual) probabilities and values involved in the construct of Yovits' model. In what follows we use Yovits' notation and define those parameters that are true or actual with an asterisk.

5.1.8.1 DM Effectiveness: Using this notation and again following Yovits et al. (1981), we define decision maker effectiveness (DME) as the ratio of average performance to maximum performance:

$$DME = \sum_{i=1}^{m} P(a^i)\, EV_i^* / (EV_k^*)_{\max} . \qquad [1]$$

We note that DME is dimensionless and ranges from zero to one if every EV_i^* is nonnegative. For the average DM, generally only positive values will result.

As the DM learns to place high probability on the alternative which has maximum actual expected value, then the DME approaches one. If the DM has no knowledge of the structure of the situation, then there is no way in which he can narrow his list of alternatives to a viable group. Thus, DME is seen to approach zero for the case where the DM has no knowledge of structure.

The term DME defines, at a given point in time, the *actual* average effectiveness of a DM in a given decision situation. The DM does not know the actual expected values EV_i^*. He may approximate his effectiveness by substituting his current estimates of his subjective probabilities and of expected values $EV_i^*(t)$ for EV_i^* in Eq. [1]. After many trials a DM becomes a good DM (his DME approaches one) and his estimate of his effectiveness approaches DME.

At the same time, in a general sense, every DM has some imprecise understanding of his effectiveness in a given situation. A DM may believe he is very knowledgeable, skilled, and experienced so that he believes that his DME is high and near unity. Or he may recognize that he knows little about the situation and his DME is close to zero. Or he may recognize that he is somewhere in between. Yovits believes that a rational DM can closely estimate his effectiveness.

5.1.8.2 Value and Effectiveness of Information: We have defined earlier the quantity of information, I(D), which is based on DM uncertainties. This quantity is DM dependent and says little about DM performance or about the value of information. Information value must be related directly to its effect on performance.

We define the *value of information*, VI, in a given set of data, D, at time t to be the change in DM average performance due to the receipt of these data. That is,

$$VI(D,t) = \text{average performance } (t) - \text{average performance } (t_0) . \quad [2]$$

This has the same dimensionality as v_{tj}, in the outcome value matrix (Figure 5.1.3-1—note—main model matrix figure) and permits us to relate information to specific measures of performance such as dollars, time, personnel, etc.

For convenience we find it more appropriate to deal with a normalized measure of value which goes from zero to one. This we will call the *effectiveness of information*, EI. This quantity differs from VI in that it is simply VI divided by EI^*_{max}, and we note that

$$EI(D,t) = DME(t) - DME(t_0) , \quad [3]$$

That is, the effectiveness of the information in a given set of data, D, at some time t is simply the change in DME due to the receipt of the data.

The quantities EI and VI can be positive, negative, or zero depending on how the *performance* of the DM may change due to receipt of the data. However, on the *average* for the DM who learns from his decisions, they are always positive since DME will increase with time and number of trials. This measure is, of course, also DM dependent, but *on the average* for a given situation for a given number of trials it is unique, dependent only on the confidence and learning factors of the DM.

We have now specified two fundamental quantitative measures which define information quantity and value. These are different quantities. The DM, knowing (or being able to estimate) his current probabilities for various alternatives and the way in which they change with new data received, can estimate the quantity of information in any data set presented to him. In fact, if the related mathematical expressions are expanded in this approach the only thing the DM needs to know is the *change* in the squares of the appropriate probabilities.

To know the actual value or effectiveness of the information, the DM must know the change in his performance. He cannot know this accurately since he does not know the actual expected values. However, he can approximate these from his estimates of EV_i^*.

5.1.8.3..External Information: We have thus far discussed the situation whereby all information which the DM uses is obtained as a result of his decisions, selection of COAs, and associated outcomes. Feedback from these outcomes provides the information needed for the DM to update his assessment of the situation. Of course, in addition, *external information* may be received which permits the DM to update his assessment. Messages and data may be received. Reports, documents, or books may be available which provide the necessary information to update his state of knowledge and to change his own matrix values and his subjective expected value estimates, as well as to establish the structure of the problem.

External information will, of course, assist in changing any or all of the various uncertainties (goal, state of nature, executional) involved in the total situation. The Yovits approach is concerned primarily with *executional uncertainty*, largely because he believes that

the extension to goal and state-of-nature uncertainty is relatively straightforward. Furthermore, he believes that consideration of the executional uncertainty and associated feedback information is fundamentally new and leads to important results and restrictions on decision making and the required information. (Yovits asserts that executional uncertainty is frequently overlooked.)

External information, when it bears an executional uncertainty, can, of course, change the DME and can also change the DM's current subjective probabilities for selecting various courses of action and, thus, his fundamental information measures. However, the external information has been obtained from the *experiences of other* DMs who have gone through similar decision making processes. Thus, it is in reality some other DM's internal information converted into external information and subsequently communicated to and used by other DMs who are considering similar situations.

In other words, in a complex system the *only* way to learn about the characteristics of the system is to make a decision, choose a COA, and compare the resulting observables with the predicted observables as we have discussed earlier. The fact that others may have gone through similar processes or that a DM can relate his current situation to previous similar situations should not obscure this fundamental point. One person's internal information may be another person's external information.

5.2 Other Perspectives on Informational Value in the Context of Decision Making

5.2.1 Informational Value Derived from a Behavioral Approach

The work of Ackoff (1958), from which the following is drawn, makes an effort to define such notions as a decision maker's "purposeful state" among others, which notions derive from a behavioral point of view. This work also focuses on understanding the decision maker's objectives, his valuation of each objective, his possible courses of action, the efficiency of each course of action in achieving each objective, and the probability of choice for each course of action. This work therefore sets the foundation for Yovits' later works (discussed in Section 5.1) which expand somewhat on the ideas developed by Ackoff. However, Ackoff's work expands on and better defines certain notions in decision making models as well as notions of value, and we, thus, include this work for completeness.

5.2.1.1 A Purposeful State: A definition of this state sets a framework for decision making. Ackoff argues that communication is an activity in which only purposeful entities can engage. Purposefulness exists only if choice is available to the entity involved and if that entity is capable of choice.

Following Ackoff, a purposeful state (S) may be defined by reference to the following concepts and measures:

I: the individual or entity to which purposefulness is to be attributed.
C_i: a course of action; $1 \leq i \leq m$.

O_j: a possible outcome or consequence of a course of action; $1 \leq j \leq n$.
P_i: the probability that I will select C_i in a specified environment, N; that is,
$P_i = P(C_i / I, N)$.
E_{ij}: the probability that O_j will occur if C_i is selected by I in N; that is, the efficiency of C_i for O_j in N.

$E_{ij} = P(O_j / C_i, I, N)$

V_j: the value (importance) of O_j to I.

Clarification of some of these concepts is necessary but we will leave the details to the next phase of this work.

5.2.1.2 Courses of Action: A course of action is not to be construed as mechanistically specified behavior. Variations in the action with respect to certain physical characteristics may not change the course of action. For example, "driving a car" may be designated as a course of action. There are many different ways of driving a car but it is frequently useful to group these into one class of behavior (in a sense, as a "fuzzy" class). Despite the variations within the class, it can be distinguished from other classes; for example, from "using a street car." A course of action may be specified with varying degrees of rigidity depending on the purposes of the research. For one purpose it may be desirable, for example, to distinguish between lefthand and righthand driving. For another purpose it may be desirable to group the use of all self-powered vehicles into one course of action.

It should be noted that the problem of specifying a course of action is essentially similar to that of specifying a physical object. For one purpose an automobile may be considered as a unit; for another it is a composite of many other units (*e.g.*, wheels, transmission, etc.), and for still another purpose it may be considered to be a part of a unit (*e.g.*, a fleet of cars). These distinctions are not unlike those that are used in Object-Oriented (OO) methods for the design of software. It may be possible therefore to apply the OO paradigm to the specification of a decision making process model and its informational components.

A course of action is said to be *available* in an environment if there is a probability of its being selected by someone, that is, if

$$\exists I_k : P(C_i / I_k, N) > 0. \qquad [1]$$

An available course of action may have no probability of being selected by a specific individual under a particular set of conditions. Then it is not a *potential* course of action for him. This is equivalent to saying that a course of action, C_1, is potential to an individual in an environment if, for one or more sets of values of E_{1j} and V_j in N, P_1 is greater than zero. Nevertheless, for some specific set of values of E_{1j} and V_j, P_1 may be equal to zero.

The relativity of courses of action and outcomes should be noted. They are conceptual constructs which may be converted into each other depending on the interests of the researcher. For example, "sawing a tree" may be considered as a course of action which yields the "falling of a tree" as an outcome. But "felling a tree" may be considered as a course of action which can yield the outcome "clearing a path." Such relativity of concepts is common in all areas investigated by science and hence does not present any unique methodological problem in this context.

5.2.1.3 Efficiency: Many different measures of efficiency are in current use. It is fairly common to use some measure of the cost, time, and/or effort required to bring about a specified outcome (*e.g.*, to complete a specified task such as "traveling one mile") as a measure of efficiency. It is also quite common to measure efficiency in terms of the portion of an outcome which is realized by the expenditure of a specified amount of money, time, and/or effort. For example, one can measure the efficiency of a machine tool either in terms of the number of units produced per dollar or in terms of the cost per unit. Thus, efficiency is commonly measured either as: (1) units of input required to obtain a specified output, (2) or as units of output obtained by a specified input. Neither type of measure is sufficiently general to be applied in all situations.

The input required for a fixed output and the output yielded by a fixed input may not be constant. For example, the number of units made per hour by a machine varies from hour to hour and the miles per gallon obtained by an automobile also varies. Hence, for a fixed input various possible outputs exist to each of which a probability can be assigned. If, in the definition of a course of action, an input is specified, then the efficiency of that course of action for a specified outcome can be defined as "the probability that the outcome will occur if the course of action is taken." This measure can always be applied in a purposeful state.

This measure of efficiency of a course of action depends on the environment and the individual involved. For example, use of skis may be efficient for self-transportation down a snow-covered hill but not so down an uncovered hill. Different individuals may ski with different efficiencies and the efficiency of the same individual may change over time (*e.g.*, by learning). Consequently, the relevant time period, individuals, and environment should be specified in designating efficiency.

5.2.1.4 Value: As in the case of efficiency there is no one measure of value or worth of an outcome that is generally accepted. Fortunately, however, such a measure is not necessary for our purposes here. Nevertheless, it is convenient to use some kind of standard measure wherever possible. A dimensionless measure of *relative* value may provide such a convenient standard. If the values (v_j) assigned to the various outcomes are all positive, a measure of relative value (V_j) for each outcome may be obtained by the following conversion:

$$V_j = \frac{v_j}{\sum v_j}. \qquad [2]$$

Then, since

$$\sum \frac{v_j}{\sum v_j} = 1.0 \qquad [3]$$

it follows that

$$\sum V_j = 1.0. \qquad [4]$$

The minimum relative value ($V_j = 0$) occurs only when the absolute value (v_j) is equal to zero. The maximum relative value ($V_j = 1.0$) occurs when all but one outcome has zero value.

In some cases negative measures of value are used (*e.g.*, cost versus profit). The following transformation may be used in such cases:

$$V_j = \frac{v_j}{\sum \left| v_j \right|}. \qquad [5]$$

In the discussion that follows we shall use the concept of relative value and assume that all V_j's are positive and, therefore, that $\sum V_j = 1.0$. All the results, however, are easily modified to cover the use of either absolute values or the case in which negative values are employed.

It is assumed here that no v_j can have an infinite absolute value. This assumption is based on an analysis of the meaning of "absolute value" which appears in (Ackoff, 1958). Following the argument presented there a value can approach an infinite magnitude only as an unattainable limit.

A purposeful state (S) may now be defined relative to the concepts which have been discussed. An individual (I) may be said to be in a purposeful state in an environment (N) if the following conditions hold:

1. There are at least two exclusively defined courses of action available in N; that is, in N for C_i, where $1 \leq i \leq m$, $m \geq 2$.

2. Of the available courses of action in N, at least two are potential choices of I.

3. Of the set of outcomes (defined so as to be exclusive and exhaustive) there is one (say, O_a) for which two of the potential courses action (say, C_1 and C_2) have some efficiency; that is, $E_{1a} > 0$ and $E_{2a} > 0$. Furthermore, $E_{1a} \neq E_{2a}$.

4. The outcome relative to which condition 3 holds has some value to I; that is, $V_a > 0$.

This definition may be summarized less technically as follows: an individual may be said to be in a purposeful state if he wants something and has unequally efficient, alternative ways of trying to get it.

If we consider an individual over a period of time it will be convenient to refer to the purposeful states at the beginning and end of that period as *initial* and *terminal* states, respectively.

The conceptual labors which have been involved in defining a purposeful state are necessary in order to make explicit the meaning of "one mind affecting another," and for enumerating the various possible types of effect. Later discussion in Ackoff shows that these effects may be defined in terms of changes to purposeful states.

5.2.1.5 A Behavioral Information Measure: The measure of information to be developed here will be related to freedom of choice; that is, it will be a function of the probabilities of choice associated with the alternative courses of action. It will be a different function, however, because of the difference between a message and a course of action. The measure here will also be a function of the number of alternative potential courses of action, m.

When we talk of the amount of information that a person has in a specified situation (state), we do so in two different but related ways. First, we refer to the number of available courses of action of which he is aware; that is, to the number of potential courses of action. For example, a person who is aware of four exits from a particular building has more information than the person who is aware of only two when there are four. The act of informing, then, can consist of converting available choices into potential choices. For example, a statement such as "There are exits at either end of this hall" may convey information in this sense. The person who has this information (*i.e.*, who has these potential choices) may or may not exercise it depending on his appraisal of the relative efficiencies of the alternative exits. In one sense, then, *information is the amount of potential choice of courses of action which an individual has.*

The second sense in which we talk of information involves the *basis* of choice from among the alternative potential courses of action. For example, an individual who knows which exit is nearer than the others has a basis for choice and hence has information about the exits. Information in this sense pertains to the efficiencies of the alternatives relative to desired outcomes (*e.g.*, a rapid exodus). Suppose, for example, that there are two exits and one is nearer than the other. If this is known and the objective (valued outcome) is to leave the building quickly, the choice is *determined* in the sense that the individual always selects the nearest exit. If he always selects the most distant exit then he is obviously misinformed (*i.e.*, he has information, but it is incorrect). If he selects each exit with equal frequency then he apparently has no basis for choice, that is, no information. In this sense, then, information is the amount of choice which has been made. Now let us make this concept more precise.

Consider the case of an individual (I) who is confronted by two potential courses of action, C_1 and C_2. If the probabilities of selecting the courses of action are equal, $P_1 = P_2 = 1/2$, the situation may be said to be *indeterminate* for I. He has no basis for choice and hence can be

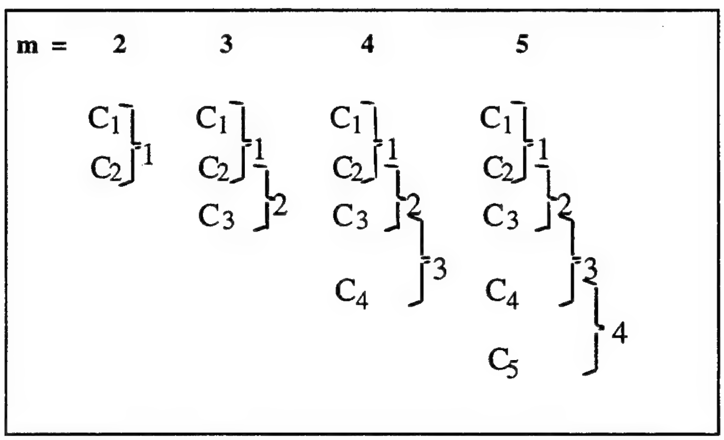
said to have no information about the alternatives. This is clearly the case when one of the alternatives is more efficient than the other. But if the two courses of action are equally efficient, the individual may have information to this effect and select each with equal frequency. Strictly speaking, however, he has no real choice in this situation since the alternatives are equally efficient. *In a situation like this—a non-purposeful state—information has no operational meaning.* Consequently, this discussion has relevance to situations in which all of the alternative courses of action are *not* equally efficient.

If $P_1 = 1.0$ and $P_2 = 0$, then the situation is *determinate* for I; all the choice that can be made has been made. The maximum possible information is contained in the state. It may not be correct but this is another matter which will be considered below.

We may define a unit of information as the amount contained in a two-choice situation that is determinate.

Let us consider the general case involving m alternative potential courses of action. In order to select one from this set, a minimum of (m – 1) choices from pairs of alternatives is required. Table 5.2.1.5-1 illustrates this fact.

Table 5.2.1.5-1 Minimal Choices for Various Numbers of Alternatives



We can conceive of the amount of information contained in a purposeful state, then, as a point on a scale bounded at the lower end by indeterminism (*i.e.*, no choice has been made) and at the upper end by determinism (*i.e.*, complete choice has been made). Location on this scale will depend on the values of P_i.

In an indeterminate state each $P_i = 1/m$. Therefore, one measure of the distance of a state from indeterminism is

$$\sum_{i=1}^{m} \left| P_i - \frac{1}{m} \right| . \qquad [6]$$

For an indeterminate state this sum is equal to zero. In a determinate state one P_i is equal to 1.0 and the remaining (m – 1) P_i's equal to zero. Therefore, in a determinate state,

$$\sum_{i=1}^{m} \left| P_i - \frac{1}{m} \right| = \left(1 - \frac{1}{m}\right) + (m-1) \left| 0 - \frac{1}{m} \right| = 1 - \frac{1}{m} = (m-1)\frac{1}{m} = 1 - \frac{1}{m} + 1 - \frac{1}{m} \qquad [7]$$
$$= 2 - \frac{2}{m}$$

The ratio of (a) the deviation of a specified state from an indeterminate state to (b) the deviation of a corresponding determinate state from that indeterminate state, then, provides a measure of the fraction of the maximum information such a state can contain, to that which it does contain. Symbolically, this ratio is:

$$\frac{\sum_{i=1}^{m} \left| P_i - \frac{1}{m} \right|}{2 - \frac{2}{m}} . \qquad [8]$$

The product of this fraction and the maximum amount of information such a state can contain—that is, (m – 1)—provides a measure of the amount of information (here symbolized by A) in that state:

$$A = (m-1)\frac{\sum_{i=1}^{m} \left| P_i - \frac{1}{m} \right|}{2 - \frac{2}{m}} = \frac{(m-1)\left(\frac{m}{2}\right)\sum_{i=1}^{m} \left| P_i - \frac{1}{m} \right|}{m-1} = \frac{m}{2}\sum_{i=1}^{m} \left| P_i - \frac{1}{m} \right| \qquad [9]$$

Now the amount of information communicated may be said to be the difference between the amount of information contained in the state of the receiver immediately preceding the communication (*i.e.*, the initial state) and the state immediately following the communication (*i.e.*, the terminal state). Let $A(S_1)$ be the amount of information in the initial state and $A(S_2)$ the amount of information in the terminal state, then the amount of information communicated, A_c is given by the following equation:

$$A_c = A(S_2) - A(S_1) , \qquad [10]$$

which may also be written in an expanded form:

$$A_c = \frac{m'}{2}\sum_{i=1}^{m'} \left| P'_i - \frac{1}{m'} \right| - \frac{m}{2}\sum_{i=1}^{m} \left| P_i - \frac{1}{m} \right| . \qquad [11]$$

where m is the number of potential courses of action in the initial state, m′ is the number of such choices in the terminal state, and P_i and P'_i are the probabilities of choice in the initial and terminal states, respectively.

A_c can take on values from – (m – 1) to (m′ + 1). Negative values represent a loss of information (*e.g.*, as in going from a determinate to an indeterminate state).

It should be noted that this measure contains no implication concerning the correctness or incorrectness of the information received. Further, it should noted that this measure is relative to a specific receiver in a specific state. The same message may convey different amounts of information to different individuals in the same state or to the same individual in different states. *Consequently, to specify the amount of information contained in a message it is necessary to specify the set of individuals and states relative to which the measure is to be made.* If more than one individual or state is involved it is also necessary to specify what statistic (*e.g.*, an average) is to be used. Generality of information may be defined in terms of the range of individuals and/or states over which it operates.

It should also be noted that messages are not the only source of information. One may obtain information by observation. For example, one may count the number of exits from a house. The measure of information suggested here is applicable to information obtained by either observation or communication.

5.2.2 Informational Value as Derived from Multi-Attribute Models

Multi-attribute utility (MAU) models, pioneered by Raiffa and his colleagues (Raiffa, 1969; Keeney & Raiffa, 1975) and by Von Winterfeldt (1975) provide another alternative framework for aiding the information management process. These utility models tie the information decisions directly to the ensuing action decisions. The value of obtaining information is determined by calculating its impact on the expected utility of the subsequent action decision. The information is assumed to change the probability distributions of the consequence sets and, in turn, to revise the expected values of the alternative actions. Nevertheless, the form of the model is again a linear additive rule. The utility of an action is considered to be an aggregate of many possible outcomes, each expressed along a set of attributes:

$$EU\ (a_k) = \sum_{\substack{states \\ h}} P(z_h) \sum_{\substack{attributes \\ i}} U_i(a_k, z_h) \qquad [1]$$

Where EU (a_k) is the expected utility of action k, P(z_h) is the probability of state z_h occurring, and U_i (a_k, z_h) is the utility function over the i[th] attribute associated with state h and

action k. The formulation is the result of several key simplifying assumptions. The decision maker is assumed to be risk neutral, so that he is indifferent between the expectation across a set of uncertain outcomes and the uncertain outcomes themselves. This allows the probabilities to be entered as simple coefficients. Also, the attributes are assumed to satisfy additive independence, allowing the linear additive form of aggregation. Tests for compliance with these assumptions can be found in Von Winterfeldt (1975) or Keeney and Raiffa (1975).

The impact of a message or item of data is to change the probability distribution of the states z_h. Once the message is received, a maximum utility action $a^*(y)$ can be identified. The expected utility of selecting an information source S then becomes (Emery, 1969):

$$EU(S) = \sum_{\substack{messages \\ y}} \sum_{\substack{states \\ z}} P(z_h)\, P(y|z_h)\, u(a^*(y), z_h) \qquad [2]$$

Here $u(a^*(y), z_h)$ is the utility of taking action $a^*(y)$ given that state z_h occurs. The utility function is again multi-attributed, but for simplicity $u(a^*(y), z_h)$ is portrayed as having already been aggregated across the various dimensions.

This type of analysis, championed by such researchers as Emery (1969), Marschak (1971) and Wendt (1969), is suited for highly structured tasks. Not only must the possible states, messages, actions, and outcomes be specifiable, but the prior state probabilities and the conditional probabilities characterizing the information system must be derivable. The sequence of decision stages can be depicted using a decision tree, as shown in Figure 5.2.2-1. The tree is folded back by associating with each possible message the maximum expected utility of the subsequent actions. This folding back represents graphically the process of EU maximization. The favored information source S is then identified by comparing the expectations taken over all possible messages.

5.2.2.1 Other Methodologies: A number of other techniques have also been proposed to model information seeking behavior. Among these are semiotic or information-theoretic models as in the Yovits work we have been referencing, (*e.g.*, Whittemore & Yovits, 1973), optimal control formulations, (Sheridan, 1976; Rouse & Gopher, 1977), queing models, (Rouse, 1975; Enstrom & Rouse, 1977) and information integration techniques (Anderson & Shanteau, 1970). Those who champion the MAU approach argue that, for the most part, these other techniques demand rigid problem structuring and continuous variables. More often, the communication decision is incompletely defined and involves choices among discrete rather than continuous alternatives. Thus, the discrete operators used in cue regression and multi-attribute utility models—matrices, difference operators, and detailed parameter enumerators—may be more appropriate. The interested reader is directed to (Steeb, Chen & Freedy, 1977) for a more detailed examination of these approaches.

5.2.2.2 Information Management Functions: The major information management functions faced by the operator are diagrammed schematically in Figure 5.2.2.2-1. The

information available consists of data regarding the aircraft, the targets, the environment, and operator and system capabilities. The information is then used by the operator to perform supervisory control actions.

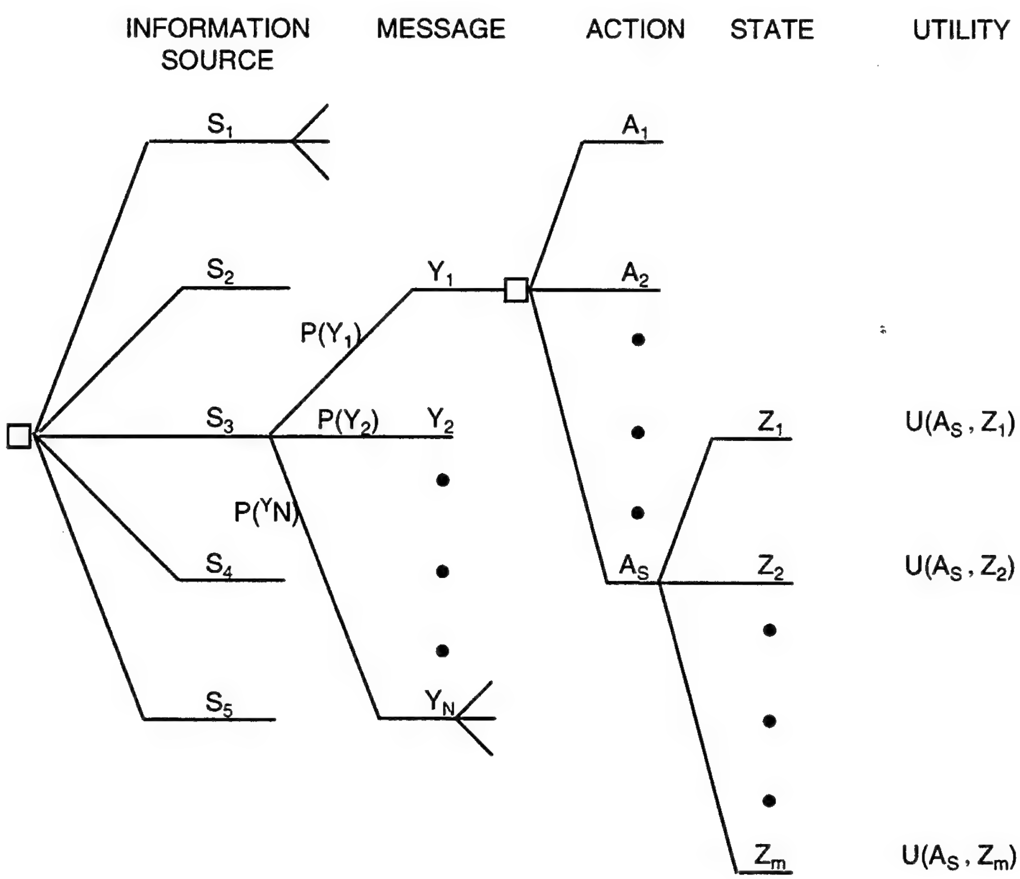


Figure 5.2.2-1 Decision Tree for Information Seeking

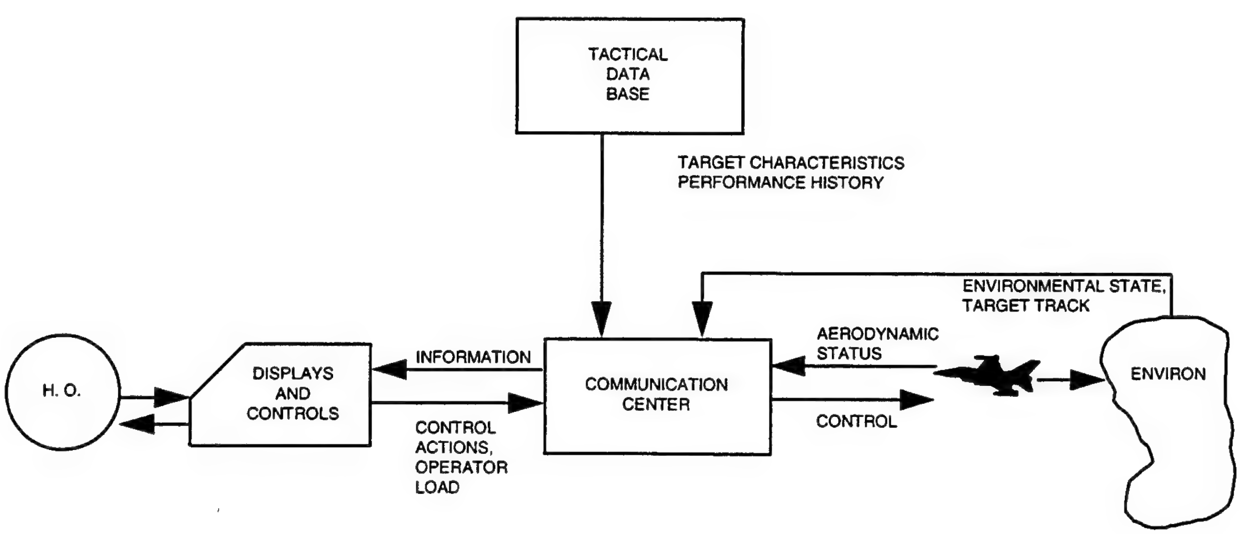


Figure 5.2.2.2-1 Major Information Management Functions

The information and control choice sequence is that diagrammed with the decision tree of Figure 5.2.2-1. This diagram is repeated with labels representative of tactical airborne operators in Figure 5.2.2.2-2, below. The multi-attribute utility formulation provides a useful basis for structuring both the information and control decisions. The specific steps of the modeling process are outlined in Figure 5.2.2.2-3. The figure shows the two sides of the modeling problem, probability estimation and utility assessment. The upper portion of the figure details the processes of probability estimation. These include delineation of the possible states of the environment, evaluating the current level of uncertainty concerning states, selecting information to reduce the uncertainty, and revising the probability estimates in light of the new data. The lower portion of the figure is concerned with outcome evaluation or utility estimation. Here the levels and importance weights for each dimension of consequence are determined.

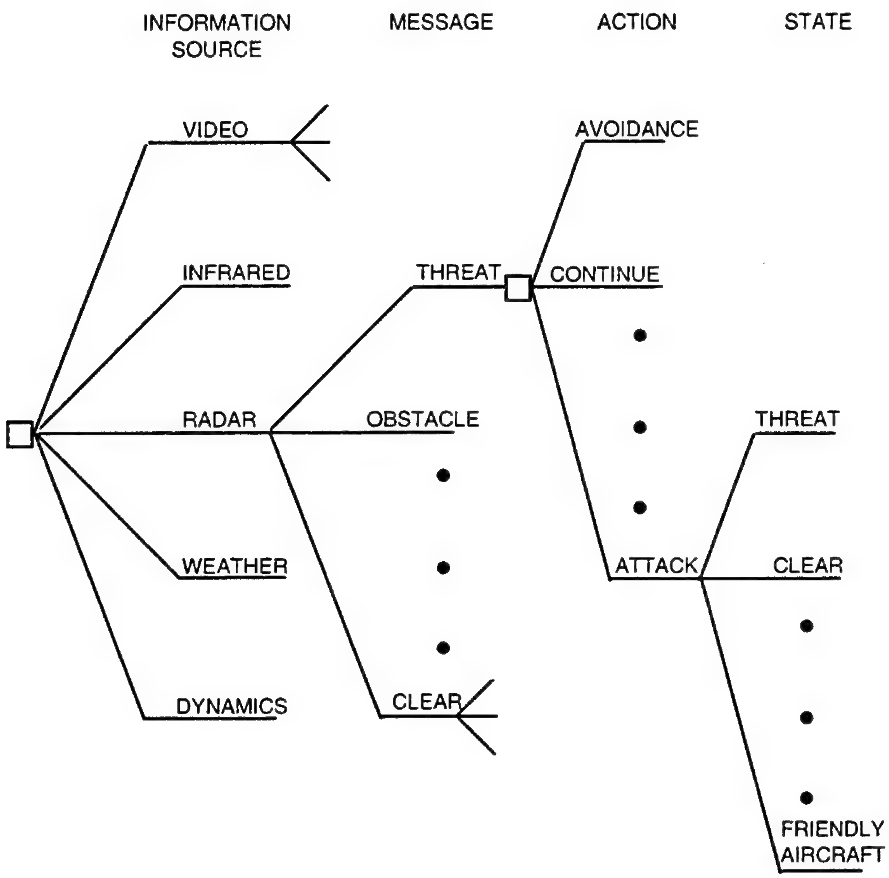


Figure 5.2.2.2-2 Decision Tree for Information Seeking in Tactical Airborne Operations

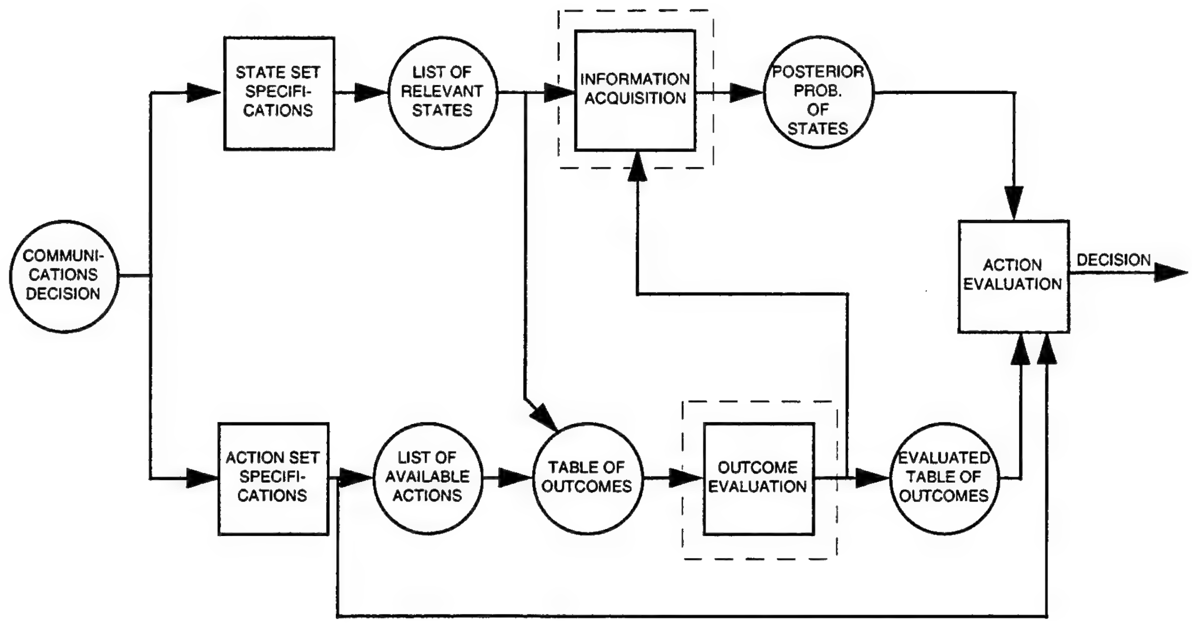


Figure 5.2.2.2-3 Decision Process Chart

5.2.2.2.1 Information Acquisition Stage: The key element in the probability estimation sequence is the information acquisition stage (enclosed by dotted lines). Figure 5.2.2.2.1-1 elaborates this stage, showing the steps that go into the choice of information and the subsequent incorporation of the datum into the situation estimate. The upper portion of the figure deals with the information source selection. The characteristics of the various available sources are determined by observation and analysis. This estimation of the characteristics of the information sources is accomplished by successive comparisons of messages received and subsequently observed states. The choice of information source is then made according to the potential impact of the information on the prior probability estimate. Once a source is selected and a datum observed, the information is incorporated into a revised situation estimate through Bayes' rule:

$$P(z_h | y_k) = \frac{P(y_j | z_h) \bullet P(z_h)}{(P(y_j))} \qquad [3]$$

where

$$P(y_j) = \sum_i P(y_j | z_h) \bullet P(z_h)$$

$P(z_h | y_j)$ is the probability of state z_h being present given that message y_j was received.

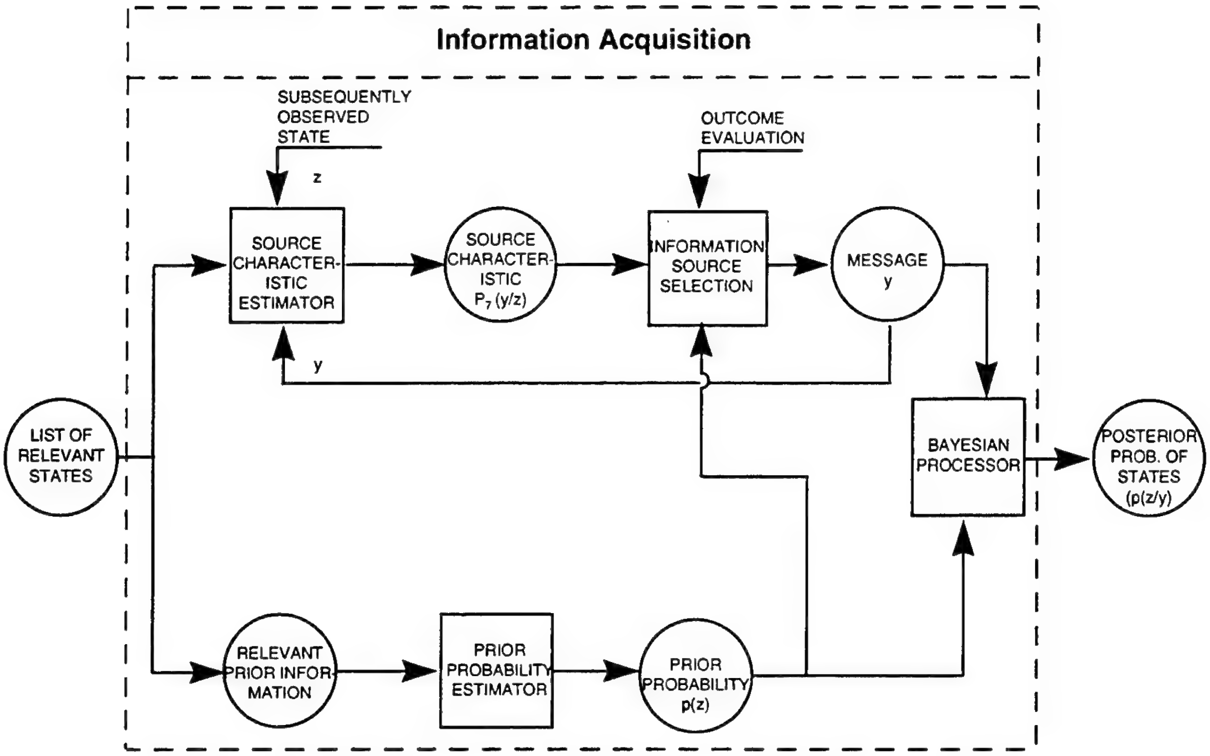


Figure 5.2.2.2.1-1 Processes Involved in Probability Estimation: An Elaboration of the "Information Acquisition" Block of Figure 5.2.2.2-3

5.2.2.2.2 Utility Assessment/Outcome Evaluation: The other major modeling process is utility assessment or outcome evaluation (also enclosed by dotted lines in Figure 5.2.2.2-3). The possible combinations of actions and states are enumerated off-line prior to a mission. The problem is then to assign consequence levels and importance weights along a predefined set of dimensions. Figure 5.2.2.2.2-1 elaborates this process. The first step is the selection of an independent, exhaustive, and predictive attribute set. The attributes are the various constituent aspects of the consequences. Each combination of information, action and outcome is associated with a set of attribute levels. This is done by observation and adjustment, just as in the determination of information source characteristics. Scaling procedures are applied to the raw consequence dimensions to arrive at normalized values. Each attribute is scaled so that its plausible range scans zero to one. These processes result in a specification of the parameters of the basic multi-attribute

$$E\ [u(x)]_s = \sum_{k=1}^{M} P(z_k) \sum_{i=1}^{N} K_i\, u_k\,(x_{ijk}) \qquad [4]$$

where

$E\ [u(x)]_s$ is the expected utility of information choice s,

$P(z_k)$ is the probability of state k with this information choice,

K_i is the importance weight for attribute i, and

x_{ijk} is the level of attribute i associated with action j and state k.

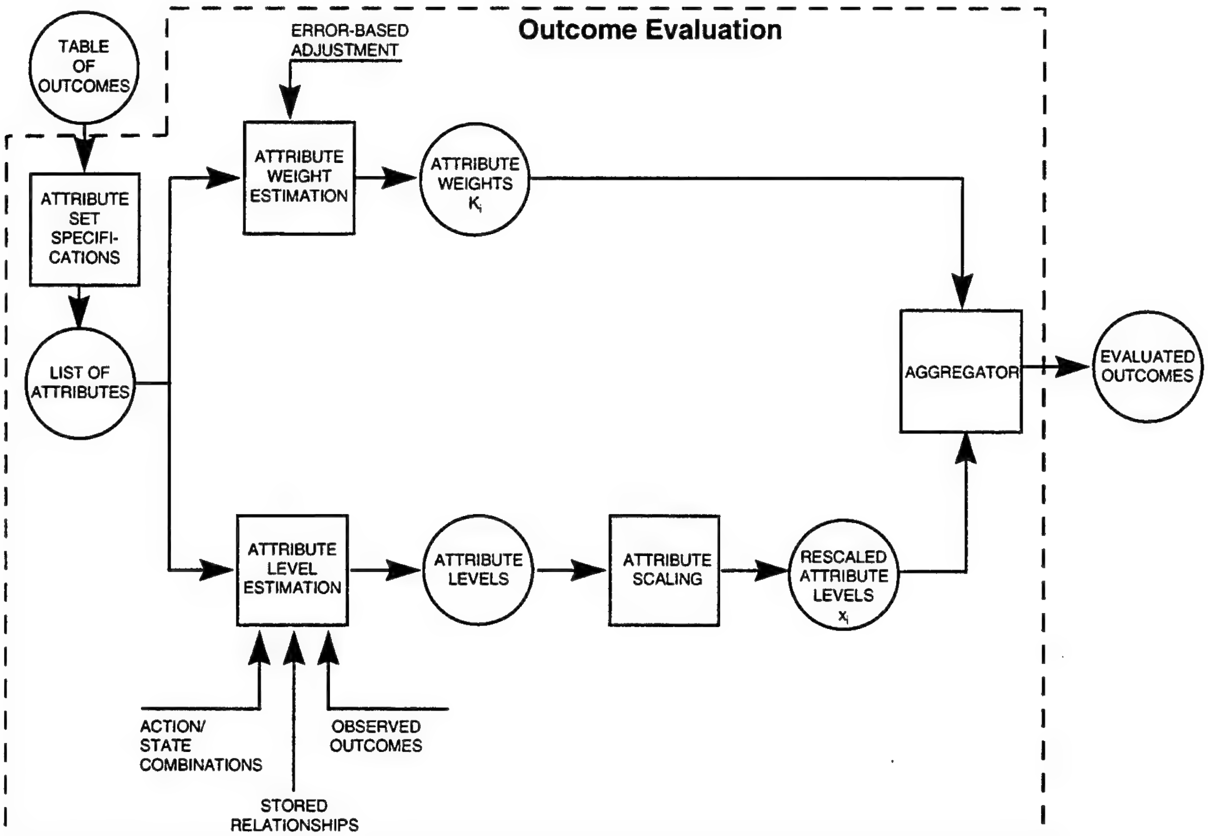


Figure 5.2.2.2.2-1 Processes Involved in Outcome Evaluation: An Elaboration of the "Outcome Evaluation" Block of Figure 5.2.2.2-3

The following sections will develop some of the specifics of the modeling cycle.

5.2.2.3 Attribute Development: The attributes of an information seeking decision are dimensions of consequence that are common to all types of the decision tree (shown earlier in Figure 5.2.2-1). These dimensions may include communications costs, equipment losses, goal attainments, future effects, and other factors. In the end, the constituent effects will be weighted and aggregated together to arrive at an overall evaluation of an outcome.

The actual choice of the attribute set is extremely important. Some researchers state that the choice of factors to include is probably of greater impact than the determination of the model form. Desirable characteristics are accessibility for measurement, independence, monotonicity with preference, completeness of the set, and meaningfulness for feedback.

Monotonicity, in this context, implies that an increase in the attribute level always results in an increase in preference. If the attribute levels are monotonic, a simplification is possible. Fischer (1972) and Gardiner (1974) note that a straight line approximation to the utility function results in minor losses of model accuracy. The estimated utility (ignoring uncertainty for now) is then a weighted linear combination of attribute levels:

$$U(a_z, z_h) = \sum_i k_i x_{ihk} \qquad [5]$$

where $U(a_z, z_h)$ is the utility of state h occurring with action z, k_i is the importance weight for attribute i, and x_{ihk} is the level of attribute i associated with state h and action k.

Information costs may comprise attributes of special note. Often, the benefits of an information acquisition are simply weighted against the costs of acquiring the information. If a net gain is anticipated, acquisition of the information is considered justified. Often, though, the costs themselves are multidimensional, comprising energy costs, time delays, equipment expenditures, and risks of detection. The scaling, weighting, and aggregating of these costs may be most easily performed in combination with all of the non-cost attributes—tactical gains, political impact, etc. Then, trade-offs among each of the factors may be performed in a single, consistent operation.

A candidate set of attributes might contain factors from five areas:

(1) Communications Costs. The expenditures associated with use of the information sources. These may include requirements of energy, equipment, and operator attention.

(2) Equipment Attrition. Consequences concerning the integrity of the vehicle. Included are fuel expenditures, system damage, and vehicle loss.

(3) Objective Attainment. The degree of accomplishment of the mission objectives. Target goals may be the area reconnoitered, adversaries dispatched, and political impact obtained.

(4) Dynamic Effects. The future consequences resulting from the current actions. These consequences may include effects on subsequent action choices, availability of future information,

(5) Subjective Needs. The operator may have propensities for obtaining (or refusing) information beyond that called for by the above factors. These preferences reflect the needs of task continuity, maintenance of load, or other idiosyncratic factors.

A useful consequence set might contain a single dimension or attribute from each of these categories. In fact, five attributes appears to be an upper limit to the number of factors a decision maker can effectively consider (Von Winterfeldt, 1975). If several factors contribute to

one consequence dimension, these factors should be combined using a single common scale-dollars, ship-equivalents, fuel quantity, etc.

Each of the attributes—communications costs, vehicle losses, etc.,—must be scaled with interval properties along a set range. The least desirable consequence that may occur is assigned a level of zero on the scale. The most desirable consequence is assigned a level of one. The weighting factors k_i should also be normalized so that the overall worst combination of factors results in a value of zero and the overall best combination a value of one.

A special situation occurs with probabilistic attributes. Assuming risk neutrality, probabilistic consequences may be computed according to their expected level. For example, the vehicle loss attribute may have three possible levels, each with a different probability of occurrence. The expected value is computed by the following additive expression:

$$E(x_{ij}) = \sum_{k=1}^{3} P(z_k) x_{ijk} \qquad [6]$$

where the parameters are defined as in Equation 2-4. Once the attributes are defined and their levels are determined, the aggregation rule must be identified. The attributes—costs, losses, delays, future impacts, etc.,—may combine in an additive, multiplicative, or more complex fashion (see Keeney & Raiffa, 1975, for a description of some of the more popular formulations). For the work here, the simple additive form, exemplified by Equation 2-5 appears to be adequate and representative. The additive form is robust, intuitively easy to understand, and simple. Also, the linear form of the additive will be seen to be amenable to estimation by pattern recognition techniques.

5.2.2.4 Consequence Level Determination: The actual level of each of the i attributes for a given outcome can be determined by mappings between predictive features and the attributes. Predictive features must be identified which are accessible to an onboard program and capable of determining the consequence levels. Mappings between the predictive features and the attributes are either pre-established or determined by observation and adjustment.

The data available to the decision program are:

(1) Directly-sensed information concerning the environmental state (weather, terrain, ECM, target track).
(2) The vehicle state (velocity, fuel, autopilot capability).
(3) The information system characteristics (capacity, noise, cost).
(4) Tactical data (technical characteristics of own and enemy aircraft, sensors and weapons; information about the operations area).
(5) Action alternatives (control responses, weapon deployment).
(6) Operator capabilities (attention, load).

A manageable subject of these features must be determined. The consequence mapping can then be refined by comparison of the predicted and actually observed consequences. The mapping can be developed either by prior definition, by regression, or by the pattern recognition techniques described in the coming section.

5.2.2.5 Attribute Weight Estimation: The policy defining factors in the model, the importance weights k_i, are parameters suitable for either elective or subjective estimation. If the consequences can be defined along objective scales (dollars, ship-equivalents, etc.), then the weights could be derived by analysis and input prior to system operation. Unfortunately, Felson (1975) states that only in a few highly structured situations can such an optimal model be derived. More often, the operator's goal structure, expressed as importance weights, must be elicited or inferred and then incorporated in the model. There are a number of advantages to such subjective estimation, particularly with respect to allocation of function. By incorporating individualized operator weights in the model, the complex evaluation and goal direction functions remain the responsibility of the operator, while the normative aggregation functions are assumed by the computer. Also, operator acceptance of aiding by the model may be increased since his preferences are incorporated in the machine decisions.

The operator's subjective weights may be defined off-line by elicitation or on-line through inference. The off-line methods include direct elicitation of preference, decomposition of complex gambles into hypothetical lotteries, and use of multi-variate methods to analyze binary preference expressions. These techniques are accurate and reliable in many circumstances, but they have a number of disadvantages when applied to operational systems. Typically, these methods require two separate stages—assessment and application. Assessment requires an interruption of the task and elicitation of responses to hypothetical choices. Problems arise with such procedures since the operator's judgments may not transfer to the actual situation; the decision maker may not be able to accurately verbalize his preference structure; and the judgments made in multi-dimensional choices are typically responses to non-generalizable extreme values (Keeney & Sicherman, 1975).

Estimation techniques relying on inference from in-task behavior may be more useful. The inference techniques can be based on non-parametric forms of pattern recognition. Here a model of decision behavior is assumed and the parameters of the model are then fitted by observation and adjustment. Briefly, the technique considers the decision maker to respond to the characteristics of the various alternatives as patterns, classifying them according to preference. A linear discriminant function is used to predict the decision maker's choices, and when amiss, is adjusted using error correcting procedures. In this way, no preference ratings or complex hypothetical judgments are required of the operator.

The adaptive nature of the estimation program is shown in Figure 5.2.2.5-1. Expected consequence vectors associated with each information source are input to the model. These consequence vectors are dotted with the weight vector, resulting in evaluations along a single utility scale. The maximum utility choice is determined and compared with the operator's actual choice. If a discrepancy occurs, the weight vector is adjusted according to the following rule:

$$\underline{k}' = \underline{k} + \lambda(\underline{x}_c - \underline{x}_m) \qquad [7]$$

where $\underline{k}'$ is the updated weight vector
$\underline{k}$ is the previous weight vector
λ is the adjustment constant
$\underline{x}_c$ is the attribute vector of the chosen alternative
$\underline{x}_m$ is the mean attribute vector of all alternatives ranked by the model above the chosen alternative.

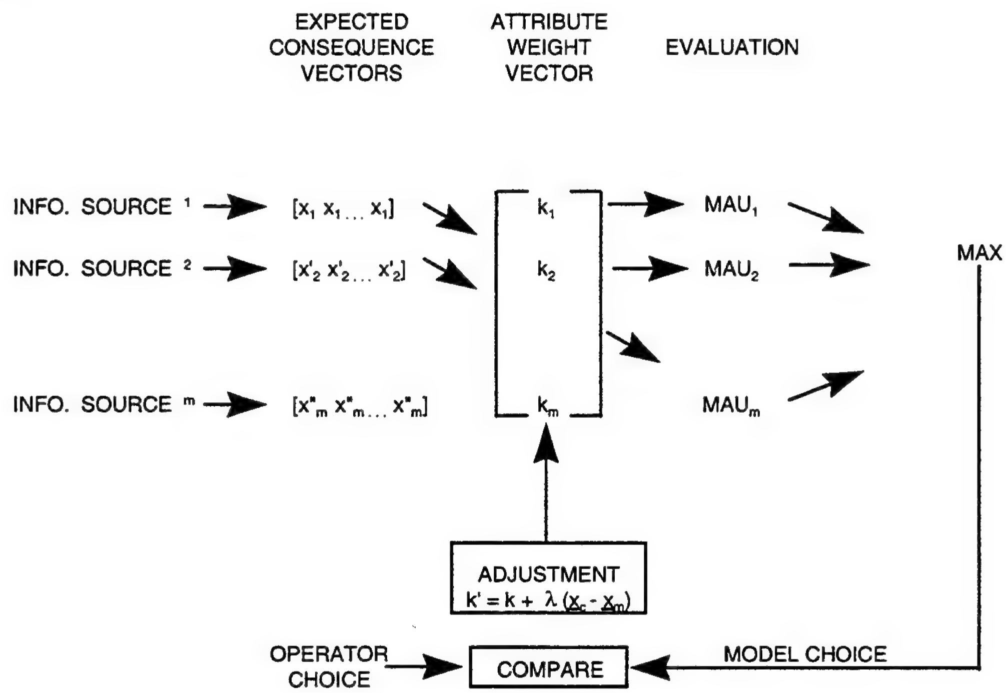


Figure 5.2.2.5-1 Adaptive Estimation Process

Ideally, the error correction moves the weight vector in a direction minimizing subsequent errors. The amount of movement depends on λ, the adjustment increment. Nilsson, 1965, describes several different forms of λ that can be used depending on the combination of speed and smoothing desired.

The type of criteria used for model training is also a major consideration. The training may be based on objective outcomes such as stock market consequences, or subjective criteria such as actual operator decisions, or on some combination of subjective and objective criteria. The approach based on both objective and subjective criteria is the most involved. In many situations, an occasional indicator of objective performance is observable. The aircraft may be lost, the target attained, or some number of subgoals accomplished. In this way, the correctness of a sequence of actions may become objectively known. The utility model would be trained subjectively prior to this by observation of the operator's choices. If the sequence of choices led to an objectively favorable outcome, the trained parameter set would be retained. If the outcome was unfavorable, the parameter set would be returned to the levels present prior to the sequence

of decisions. In this way, objective criteria would guide overall training, but the explicit decision-by-decision policy for information management would be subjectively derived.

Of course, the adaptive techniques of estimation described above are warranted only if repetitive decisions are available for training and if the differential weighting of attributes is important. In cases where only a few non-repetitive decisions will be made, off-line estimates of the weights k_i are favored. Here, techniques such as direct estimates, hypothetical lotteries, or multiple regression are used for estimation prior to the mission. It is assumed with these techniques that the system requirements will not change after the estimates.

Questions concerning the importance of differential weighting are more basic. Unit weighting schemes (in which all weights k_i are set equal to 1.0) have been found to be quite effective in certain circumstances. Errors in the model form, positive correlations between variables, and small sample sizes all reduce the predictive capabilities of differential weights compared to unit weight (Einhorn & Hogarth, 1975). Essentially, the more precise and parsimonious the model, the more important differential weights are.

Unit weighting schemes are expected to see only minor application in aiding advanced aircraft operations. Careful selection of attributes minimizes intercorrelations between variables, and the correlations that do occur should tend to be negative. For example, in most cases costly information is generally more informative than inexpensive information, and equipment attrition tends to be negatively correlated with goal attainment. These circumstances favor inferred weight models. Unit weighting schemes should primarily be useful as starting points for estimation, or as strategies for situations in which a great deal of noise is present.

5.2.2.6 Probability Estimation: The major probability parameters requiring estimation are the prior probabilities P(z) and the conditional probabilities P(y|z). The priors are the probabilities of state z in a particular situation. The conditional probabilities deal with the likelihood of receipt of message y if state z is present. Both of these forms of probabilities can be estimated from frequency counts.

A second area of uncertainty concerns the consequence levels associated with a given message and state. These are the performance probabilities and are derived from stored data: detection range, target hardness, personnel performance, system reliability, guidance system accuracy, etc. The probability of outcome given the message received can be computed for each set of actions. Comparison of the messages received, actions taken and the consequences subsequently observed provide the necessary data.

5.2.3 Informational Value in the Sense of "Purchase Cost"

Another way to gauge the value of information is in the sense of an assignable cost for the "purchase" of a piece of information. This is informational value in the context of information-seeking. This perspective is consistent with the current notion of "information pull" for future C2 systems. (The "C4I for the Warrior" vision from the JCS in 1990 describes the idea of "warrior pull" and "infosphere push" in describing one future vision of the role of advanced

information processing on C2, and on the flow of information within a notional "infosphere" or communications backbone which permits selective information extraction—"pull"—from it. Presuming there is an assignable cost to this action, then the cost of a "pull" of a quantum of information would be in proportion to its value.) We draw here extensively on the work of Wendt to quantify one model of informational value in this sense of "purchase price" (Wendt, 1969).

In information purchase tasks, the subject decides between bets in the sense that he chooses between a risky bet without the information or with little information, and a less risky one with more information. This allows him to revise the probabilities of the outcomes although he has to pay for it. Research on choices among bets has shown that subjects may have probability preferences (Edwards, 1953), and that their utility function may deviate somewhat from linearity, though negligibly little in the region of small monetary gains (*e.g.*, Lindman, 1965; Tversky, 1967). The main finding in research on human probability estimation and revision is that people are conservative estimators in the sense that they do not extract from the data as much certainty as the data justify. (In an IW environment where, unless advised to the contrary, one would more broadly hold information as suspect, this behavior may actually have some beneficial value in leading to conservative decision making.)

Does human conservatism in probability revision affect information seeking behavior? Or are people near-optimal in this as in many other decision tasks? Unlike the research of Wendt, earlier studies in information purchase have been experiments with optional stopping (*e.g.*, Becker & McClintock, 1967; Green, Halbert, & Sayer-Minas, 1964; Irwin & Smith, 1957; Swets & Green, 1961) where the subject may buy, for a prespecified price, an item of information that will, on the average, reduce his uncertainty about a decision that he must eventually make. After observing the first item of information, he may buy another, and after that another, and so on until he decides to stop. This is a rather complex, hard-to-understand situation. Moreover, the datum obtained in such optional-stopping experiments, the subject's stopping point, is uninformative about the interesting question: how valuable did the subject consider each datum at the time he bought it? Experiments with optional stopping have found people seeking both too much and too little information, but *seldom the optimal amount* as prescribed by the normative model of expectation maximization. In spite of that, they do rather well with respect to their final payoff. This is due to the fact that the expected value functions in these experiments are rather flat around their maxima but this may not be true in military decision problems of interest, or in general.

5.2.3.1 The Theory of Fair Cost of Information for Two Hypotheses and Binomial Data: How much should a subject be willing to pay for a datum? The fair cost C(Z) of information from a data source Z in a decision situation is the increase in expected value due to knowledge of a datum z_k from that data source Z; *i.e.*, the expected value of the decision D made with information from Z, EV(D | Z), minus the expected value of the decision without the information from Z, $EV(D \mid \bar{Z})$:

$$C(Z) = EV(D \mid Z) - EV(D \mid \bar{Z}) \qquad [1]$$

(*e.g.*, see Edward & Slovic, 1965; Peterson & Beach, 1967; Raiffa & Schlaifer, 1961). In Wendt's approach, the decision to be made is between two actions—a binary choice case—a_i, $i=1,2$, and the true "world state" or situation can also be in one of two possible states s_j, $j=1,2$. In this case the Value of any decision has a payoff, $V(a_i, s_j)$. Wendt then calculates the expected values over the possible states of nature with and without a piece of information z_k from data source Z. Thus, there is a conditional probability $P(s_j \mid z_k)$, a posterior probability of state s_j given the information z_k—so z_k aids in determining the situation upon which action decisions depend—this is its value.

It is shown in Wendt that the choice of action will be influenced by the occurrence of a datum z_1 or z_2 only if those particular values of information influence the choice of action; this condition establishes pairs of inequality relations (not shown here) whose inequality signs must be changed by the awareness of a datum z_1 or z_2. This is the case if the likelihood ratio $L = P(z_1 \mid s_1)/P(z_1 \mid s_2) = P(z_2 \mid s_2)/P(z_2 \mid s_1)$ is large enough so that

$$\frac{P(z_2|s_1)}{P(z_2|s_2)}\,\frac{P(s_1)\,R(a_2,s_1)}{P(s_2)\,R(a_1,s_2)} < 1\ , \qquad [2]$$

and hence

$$P(z_2 \mid s_1)\,P(s_1)\,R(a_2, s_1) < P(z_2 \mid s_2)\,P(s_2)\,R(a_1, s_2)\ , \qquad [3]$$

so that the choice of action a_1 is recommended if z_2 occurs. In Eq [2], R is the "regret," formed by subtracting from each payoff the maximum column entry, and changing signs (see Wendt, 1969, p. 432.). This change, however, is only possible if

$$1/L = P(z_2 \mid s_1)/P(z_2 \mid s_2) < P(s_1)\,R(a_2, s_1)/P(s_2)\,R(a_1,s_2) = Q\ , \qquad [4]$$

and hence $L > Q$. Q is the value of a constant dependent on prior probabilities and regrets (the inverse of a payoff) given by : $Q = \{P(s_1)\,R(a_2, s_1)\} \,/\, \{P(s_2)\,R(a_1,s_2)\}$

Following Wendt, in general, $|\log L|$ (to any base) would be an appropriate measure of the *"diagnosticity"* of a datum z, that is, of the ability of z to discriminate between s_1 and s_2: it is 0 for $L = 1$, and increases as L deviates from 1; *i.e.*, as data become more diagnostic in one or the other direction, and aid in influencing an action a_1 or a_2. Since in this binary-type decision framework $|\log L|$ is monotonic with $P(z_1 \mid s_1)$, Wendt uses $P(z_1 \mid s_1)$ as an (ordinal) measure of the diagnosticity of the data source. A data source is completely undiagnostic if $P(z_1 \mid s_1) = .5$, and completely diagnostic if $P(z_1 \mid s_1) = 1$. Whenever $L \geq Q$, a linear increase in $P(z_1 \mid s_1)$ causes a linear increase in $EV(D \mid Z)$ [or a linear decrease in the expected regret, $ER(D \mid Z)$], and thus, a linear increase in C(Z). The slope of these lines is

$$b = P(s_1)\,R(a_2, s_1) + P(s_2)\,R(a_1, s_2)\ , \qquad [5]$$

as can be seen from the expanded version of Eq. 1 as described in Wendt: once the minimizing over a_i is accomplished, C(Z) is linear in $R(a_i, s_j)$ and $P(z_k| s_j)$. Finally, then, for the case under consideration, Eq. [6] shows how to calculate fair cost of information, dependent on its diagnosticity:

$$C(Z) = \begin{cases} 0 \ \ for \ \ P(z_1|s_1) \le Q/(1+Q) \\ \min\limits_{a_i}[P(s_1) \ R(a_2, s_1), \ P(s_2) \ R(a_1, s_2)] \\ \quad - [1 - P(z_1|s_1)][P(s_1) \ R(a_2, s_1) + Ps_2) \ R(a_1, s_2)] \\ \quad otherwise, \end{cases} \qquad [6]$$

with Q as specified previously, and $P(z_1 \mid s_1) \geq .5$.

5.2.4 Informational Value via the Information Indexing Approach

The value of an item of information can be assessed in terms of the amount of entropy, or uncertainty, it reduces. In any particular task the amount of uncertainty reduced may be evaluated with respect to the stimulus, the response, or both in combination. Depending upon which reference is selected, numerous measures of information value are available *provided* the decision making situation is well defined, *i.e.*, clearly-specified, mutually exclusive and collectively exhaustive stimulus and response descriptions are available. When this requirement is satisfied, matters of computational convenience normally dictate selection of a measure. Thus, information (bit) or signal detection (signal/noise ratios) measures are used when the reduction of stimulus uncertainty is the prime consideration, and simple and conditional probability measures associated with statistical-decision theory are used when reductions in response equivocation are sought. When the behavior of human decision makers becomes important, additional measures can be derived from descriptive choice behavior theories of Edwards (1954), Siegel (1961) and others, as well as the numerous extensions of Estes' (1959) statistical learning theory.

5.2.4.1 Measuring Information Value in Complex Tasks with Fuzzy Alternatives and Information: For a large class of practical decision making tasks, however, the situation is noticeably different. Specifically, comparable metrical assistance is lacking when assessing information value in situations where responses must be chosen from a large set of alternatives *which are no more than loosely specified*, if at all, and/or where each response must be made on the basis of the appearance of a single stimulus, or a mixture of, stimuli, in a *poorly defined stimulus set*. Examples of such situations include military commanders acting on the basis of intelligence supplied to them and business executives deciding how to alter their product line to meet a changing market and competition.

In attempting to measure information value in such practical decision situations, at least three alternative approaches are available:

- The *first* involves *comparison* of information items against standardized lists of "information requirements" derived from detailed task analyses. A certain amount of quantification can be introduced in the form of summed binary attribute

comparisons where judgments are made for each type of information item concerning its appearance or non-appearance on the lists. Occasionally, items on the lists have been scaled with respect to a number of criterion variables such as time of need, level of detail needed, etc. When such scaling has taken place, attribute comparisons can be extended to some type of *weighted checklist score,* although problems are met in attempting to take account of multiple criteria and, consequently, multiple weighting terms.

- The *second* approach is one of brute force. By the use of large scale computer simulations the worth of various types of items is assessed in terms of their observed effect on performance. Usually, however, the problem of multiple criteria remains because the performance indices are highly specific to particular situations and do not generalize well to other types of operations. One distinct advantage of this brute force technique is that any evaluation of information worth is tied closely to highly relevant criteria of performance adequacy.

- A *third* approach would employ a single general criterion measure. In such an approach, overall utility of-information judgments from a large sample of experienced commanders, could be defined from surveys, and normalized to derive a quantitative worth of information equation within which all information could be eventually expressed in terms of the same *utility measure.*

5.2.4.2 The Information Indexing Approach: Encouraged by the above findings, McKendry, Hurst, and Achilles (1964) proposed an information evaluation technique which assumes that *an information utility scale can be constructed from the responses of experienced decision makers.* Specifically, these judgments are quantified by the use of psychometric scaling techniques (Edwards, 1957; Torgenson, 1958) to evolve information value estimates which can be inserted into a simple equation to yield a single value score for any given information mixture. Their technique, termed an *"information indexing"* approach, rests on two assumptions:

- First, despite the apparent diversity of information items, all vary along a single underlying dimension of utility, or worth, with utility being defined as the amount of assistance given in selecting an appropriate course of action.

- Second, subject (Ss) perceptions of utility can be reliably scaled, and when items are so arrayed a sizable, positive correlation exists between perceived worth and performance adequacy. Also, when rational value can be measured, a similar correlation exists between perceived value and rational value.

As a convenience in preparing materials to be judged by Ss as well as a means of reducing substantially the number of judgments to be made, information is first subdivided into roughly equal units called "items." Usually, the definition of an item is situation specific; for example, in the case of surveillance systems, McKendry et al. (1964) defined an item as "an observation made over a specific uninterrupted interval of time about a particular physical thing or an observable attribute or characteristic of that thing, the observation being made by a single

sensing device, including man ." This research team found when intelligence messages from an actual large scale fleet exercise were decomposed into items by three judges who worked independently, better than 80% agreement between judges resulted in what was or was not called an item by itself. Also, better than 90% agreement between judges resulted when the final list of items was sorted into nine content categories. In the first use, agreement was defined as a specific portion of a message being called an item by itself or part of an item; in the second instance, agreement meant the same item was assigned to the same content category by all three judges.

To save time, Ss judge an average value for all information items in the i^{th} category. Thus, by simply counting the number of items and multiplying by the average judged value per item, a total value score can be computed or any single grouping of items, whether the grouping be found in a single message (Equation 1) or in a group of messages (Equation 2).

$$\beta = \sum_{j=1}^{n} k_j \, \alpha_j \qquad [1]$$

where β = worth of information mix contained in a message

n = number of content areas in message

kj = number of items in jth content area

α_j = average perceived value of items of information in j^{th} content area

$$B = \sum_{\beta=1}^{\beta=N} \beta = \sum_{i=1}^{N} \sum_{j=1}^{n} k_{ij} \, \alpha_j \qquad [2]$$

where α_j is as previously defined

k_{ij} = number of items from j^{th} area contained in i^{th} message

N = number of messages

Implications

The information indexing approach as originally proposed has a number of important corollaries. First, additivity of information worth is retained, thereby making it possible to achieve the same B score by widely divergent information mixtures. Second, it is assumed that the worth of items in a class is independent of the presence or absence of items in other classes.

6. ERRORS IN HUMAN DECISION MAKING

In the previous section we have defined the decision making task in functional terms, *i.e.*, what are the states of nature, the possible actions, and the values of the resulting outcomes. Based on these definitions, we have introduced measures of the value of information to the decision system. Now we must go beyond a functional description and explore the alternatives for allocating the various functions between human and automated decision components, informed by the models of the human functioning in adversarial systems developed in Section 3. Specifically, we need to explore the possible decision making errors, and how they are influenced by humans and automated systems as decision makers.

6.1 What is Error?

Reason (1990) concentrates on human error rather than error in general, but we can amend his human error definition (p. 9) as follows:

Error is when a planned sequence of activities fails to achieve its intended outcome, when failure cannot be attributed to a chance agency.

Note that this defines three elements:

1. A goal or intention, *i.e.*, the system is purposive
2. A set of actions is chosen
3. An outcome of value is implied

These elements can all be seen in the model of Section 5, where decision was defined as the choice of a series of actions, based on a value structure (intentions) for outcomes. Errors are, thus, occasions where the "correct" action was *not* chosen. Again speaking specifically of human error, Woods, Johnssen, Cook and Sarter (1994) state that "error" is a judgment made in hindsight. It is, thus, assumed possible to evaluate the quality of a decision (*i.e.*, determine if it was an error) by reference to some external, but lagged, validation criterion where "truth" about the whole situation was eventually discovered. As evidenced by legal inquiries into major system failures (Challenger, Vincennes, Bhopal, Herald of Free Enterprise), this external validation is possible in principle, but difficult and costly in practice. This idea is embodied in the concept of a criterion against which decision making performance can be judged. Hollnagel (1997) gives three parts to an error definition:

1. A performance standard or criterion
2. An event or action
3. A degree of volition

He discusses why each of these may be difficult concepts in a theoretical development, but does emerge with a second distinction useful to our thesis: error genotypes and phenotypes.

The genotype is a (generic) cause of the error, while the phenotype is the (specific) manifestation of that cause in a particular system. Those who must deal with human error are either trying to infer genotypes form phenotypes (incident investigation) or infer phenotypes from genotypes (incident prediction). In data-fusion supported adversarial systems the immediate need is for incident prediction, so that one must start with the genotypes of erroneous action.

6.2 Models of the Human Decision Maker

In Section 5 we developed a normative model of decision making: it is not specifically a model of the human decision maker. In the 1950's to 1970's psychologists and human factors engineers tended to model humans as if they were normative decision makers, both in how they combine evidence from several sources (Bayes Theorem) and in how they choose among alternatives having different probabilities and utilities (utility maximization). It was found that although people processed information in ways which correlated with these normative models, the models themselves lacked predictive value. Humans were seen as trying to optimize, but failing: *i.e.*, humans were modeled as degraded optimizers. These models still predict reasonably well in the small-scale decisions involved in simple repetitive tasks, such as movement control and inspection, but tend to completely miss the point where decisions become larger in scope, and where the decisions are made by humans with high levels of expertise. For example "rational" models of consumer behavior are no longer used by economists. Maximizing net long-term gain is not a good predictive description of real-world decision behaviors.

The unwarranted assumptions of normative theory when applied to human decisions are paraphrased from Reason (1990, p. 37-38):

1. People have consistent utility functions
2. People have exhaustive knowledge of possible alternatives
3. People can create consistent joint probability distributions relating alternatives to actions
4. People choose alternatives so as to maximize subjective expected utility.

In fact, much data shows that expert decision makers typically start from an entirely different viewpoint: can I recognize a known scenario for which I have ready-scripted prototypical solutions? Such a short-cut means a tremendous saving in cognitive workload. It is as if a climber searching for a path up a mountain recognized a known "reasonable" route rather than systematically listing and evaluating all possible routes. We can attempt to retain the normative framework by adding a condition of minimizing cognitive workload to our decision maker's objective function, but it is simpler to start from the more realistic view that experts have stored a set of satisfactory (but not optimal) short-cuts, and attempt to recognize a set of conditions which will lead rapidly to one of these. This leaves the human as a heuristic decision maker rather than a normative optimizer. But there is no reason that an instantiation of a decision system cannot combine humans and automation so as to take advantage of these unique human characteristics within an framework that is normative at the systems level.

Because people tend to behave heuristically (Tversky & Kahneman, 1983) and to specifically use situational recognition (Klein, 1993), we can list the ways in which their decisions deviate from what a systems view would consider optimal. Note that we are modeling human performance, not merely errors. These decision tendencies can well become errors in cases where our cognitive shortcuts based on bounded or reluctant rationality lead us into actions which were (at least in hindsight) seen to be errors. First, however, we need to consider the nature of human error.

6.3 Models of Human Error

As noted in Section 6.1, errors imply both intention and action. Indeed an early classification by Norman (1981) divided error genotypes into:

Mistakes: following a wrong intention

Slips: correct intention but wrong action

Combining this with Rasmussen's (1983) three levels of human functioning (skill based, rule based, knowledge based), and adding specific memory retrieval failures (lapses), brought Reason (1990) to three basic error types in Table 6.3-1:

Table 6.3-1 Error Genotypes, Adapted from Reason (1990)

Level	Error Genotypes
Skill-based	Slips, Lapses
Rule-based	Rule-based mistakes
Knowledge-based	Knowledge-based mistakes

These form the basis of expansions by Reason, Hollnagel and others into more detailed lists or taxonomies of error types. We will provide appropriate summaries of them and note how they relate to our adversarial model and situation awareness.

Based on models of the human decision maker, the following are non-normative tendencies resulting from bounded rationality, found typically in skilled decision makers. They are organized by the stage of decision behavior where they are most likely to evidence themselves. We start with the decision maker actively attending to (or searching) alternative information sources, retrieving possible hypotheses/choices from memory, filtering or weighting the evidence, making the choice of actions, and interpreting the results of the decision. We do not necessarily imply that these stages are strictly sequential. Indeed, initial choice of actions can (and does) affect the search for confirming evidence.

1. **Observing or Searching of Sources of Information**

1A. Salience Bias: Because we only attend to a limited number of sources, we tend to choose them based on their salience. Particularly under time pressure, the largest/brightest/ best positioned source can command undue attention.

1B. Persistence Bias: We tend to give more attention to sources which have proven useful in the immediate past.

1C. Absence Bias: There is a tendency to ignore sources where the *absence* of an indication is diagnostic. This may be part of a broader tendency to difficulty in dealing with reasoning from negative events.

2. **Accessing Solutions in Memory**

2A. Availability Heuristic: The ease with which previous instances or solutions can be brought to mind biases the solutions available. Thus, hypotheses/solutions which have been recently reinforced tend to be accessed most frequently and strongly.

3. **Filtering on Weighting of Information**

3A. Representativeness Heuristic: People tend to overweight evidence based upon the similarity of the presented set of information to the information set expected from a well-known hypothesis.

3B. Elimination by Aspects Bias: We quickly reduce the number of hypotheses and information sources we consider by focusing on a reduced set of information sources. Others are eliminated because they have no ready fit to solutions available from memory.

3C. "AS IF" Heuristic: There is a tendency to treat all sources of information "as if" they had the same diagnosticity, or ability to reduce the hypothesis set being considered. Clearly, in practice some sources *are* more diagnostic than others.

3D. Probability Perception Biases: Humans are not good at estimating probabilities, either in an absolute or relative sense. (They are even less comfortable with the concept of conditional probabilities.) For example, the probability of an event is over-influenced by recent events, and the salience of event reports. Another source of probability estimate bias arises from the need to rationalize our own behaviors (*e.g.*, smoking or fast driving).

4. **Making a Choice of Action**

4A. Working Memory Limitations: There is only a relatively small capacity available for active consideration and manipulation of input. Working memory needs active rehearsal (at least for some aspects) and is perceived as cognitively costly to use, especially for prolonged concentration on complex reasoning.

4B. Confirmation Bias: Once a hypothesis or action has been tentatively chosen, our search for confirmation leads to only certain selected sources. We will tend to attend only to those sources which tend to confirm that hypothesis. Wickens (1992, p. 278-79) describes this as *mental inertia* or *cognitive tunnel vision.*

4C. Satisficing: While not a bias, the selection of a feasible solution early in the decision process can lead to early termination of the search for solutions.

4D. Reversed Reasoning: Humans do not do well in causal reasoning. We have difficulty distinguishing between forward and backward chains of reasoning.

4E. Groupthink: This is presented as one example of clearly pathological decision making, such as learned helplessness, myths of invincibility, etc. In groupthink, the dynamics of the surrounding group of people can cause repression of adverse evidence, or lead to unwarranted confidence in the decision.

4F. Attribution Error: We are more inclined to attribute an event or state to causal factors than to chance, and, thus, see coincidences as conspiracies. Even within this tendency, we over-attribute to individual characteristics and under-attribute to situational characteristics.

5. Interpreting Decision Results: Feedback

5A. Misleading Feedback Attribution: When given feedback about outcomes of decisions, we again tend to under-attribute to chance. Thus, we may have been "right" purely by chance, but this feedback will reinforce the whole process that led to the decision.

5B. Selective Feedback Perception: We tend to pay more attention to feedback that we can interpret as being supportive of our decision.

5C. Interpreting Delayed Feedback: In calibrating the success of our decision process, we have more difficulty using feedback that is delayed. As some delay is inevitable, feedback may reinforce our *memory* of the decision process rather than the decision process itself.

While this may appear to be a long catalog of biases, it can be extended and linked to even longer lists of error-possibilities (*e.g.*, Hollnagel, 1997). For our purposes, though, this listing can provide sufficient guidance to assist in the design of adversarial systems.

6.4 Application of Error Types to SA Model

So far we have presented models of human decision making as recognition guided, using bounded rationality, and occurring at multiple levels of skills, rules and knowledge. From

these we have enumerated (some) error genotypes, and now need to apply these to our model of the human in an adversarial situation.

Using the Situational Awareness model from Section 3 (Figure 3.1.4-1) we can see that three levels are proposed:

SA Level 1:	Perception of Elements in the Environment
SA Level 2:	Comprehension of the Current Situation
SA Level 3:	Projection of Future Status

To this we can add a fourth level of choice of action and interpretation of feedback. For each of these levels we can logically state its inputs and outputs, and hence list its main failure modes. These failure modes will be the error phenotypes, *i.e.*, how the genotypes manifest themselves in SA. We can then relate our list of biases (or genotypes) to the failure modes to determine where friendly decision makers need aid from automated devices, and conversely how to confound an adversary with an (assumed) inferior level of technological competence.

Table 6.4-1 gives the outcomes and logically-possible error modes at the three SA levels. Although this is not an exhaustive listing, it can be seen that a number of error types are pervasive, particularly **4A: Working Memory Limitations**. Lack of correct sampling is shown to be related (naturally) to observing biases, while model structure is prone to filtering or weighting biases and feedback (again naturally) to feedback biases.

Within this general picture, exploitable patterns emerge. If elements are not sampled correctly, then interface design can exploit salience characteristics to increase utilization of neglected information sources. From an adversarial point of view, we can look for ways to make misleading elements or cues more salient, as well as to exploit persistence bias. This latter can be accomplished by the typical military tactic of providing the enemy with enough successes to ensure persistence of attention to the (now wrong) cues. Such a tactic also exploits **2A: Availability Heuristic** and **4F: Attribution Error**. These help to ensure that the enemy's sampling is false, that his model is wrong, and that it remains wrong by poor use of feedback.

Premature conclusions have been related to many errors, both processing limitations and the liability to take salient but wrong shortcuts, known as "strong but wrong." However, this is the very bias which allows the experienced commander to make rapid, and usually accurate, choices. Here, automated systems can aid the human commander by pointing out inconsistencies between the diagnosis (and chosen action) and the best estimates of the current information from *all* elements in the perceived world. This help can prevent false premature conclusions while not interfering with those premature conclusions that do not contradict known information.

The ubiquity of **4A: Working Memory Limitations** is addressable by hardware and interface design that exploits the human's pattern recognition abilities. This integrated rather than separate display using Wicken's proximity/compatibility principle (Wickens, 1992) will

reduce the load on working memory and allow more accurate information processing. Such systems are currently being exploited in fighter cockpits specifically to enhance situational awareness.

Table 6.4-1 Processing Steps, Outcomes and Possible Errors at Each SA Level

SA Level 1: Perception of the elements in the physical environment Outcome: Each element in the environment is correctly sampled, its information is correctly perceived, and stored	
Processing Steps	**Logical Error Modes**
1.1 Element Sampling	Element not sampled Element not sampled for long enough to estimate parameters Sampling frequency too low to estimate dynamics of element
1.2 Information Perception	Data below threshold of human or sensors Data perceived wrongly
1.3 Information Storage	Data perceived but not stored Data perceived but forgotten before storage
SA Level 2: Comprehension of the current situation Outcome: An accurate model of the world is constructed, and populated with accurate data from environmental elements	
Processing Steps	**Logical Error Modes**
2.1 Form Model Structure	Inadequate model structure - too simple Wrong model structure
2.2 Populate model with data	Data not remembered for transfer Data transferred incorrectly
SA Level 3: Prediction from model of future status Outcome: Correct prediction of future states by running model forward in time	
Processing Steps	**Logical Error Modes**
3.1 Prediction using model	Unable to predict - cannot run model Incorrect prediction 1. Does not understand model Incorrect prediction 2. Premature conclusions
SA Level 4: Choice of action and feedback from world Outcome: Correct command/control actions chosen, feedback obtained and correctly interpreted	
Processing Steps	**Logical Error Modes**
4.1 Choice of action	No action chosen Incorrect action chosen
4.2 Use of feedback	No feedback obtained Feedback delayed Feedback misinterpreted

From this table, we can add the possible biases at each level and processing step to give the results shown in Table 6.4-2

Table 6.4-2 Processing Steps, Possible Errors and Relation to Error Genotypes

Processing Steps	Logical Error Modes	Related Error Genotypes
1.1 Element Sampling	Element not sampled	1A, 1B, 1C, 4B
	Element not sampled for long enough to estimate parameters	3D
	Sampling frequency too low to estimate dynamics of element	3D
1.2 Information Perception	Data below threshold of human or sensors	
	Data perceived wrongly	1A, 3D
1.3 Information Storage	Data perceived but not stored	4A
	Data perceived but forgotten before storage	4A
2.1 Form Model Structure	Inadequate model structure - too simple	2A, 4A, 4C
	Wrong model structure	2A, 3A, 3B, 3C, 3D, 4A, 4C
2.2 Populate model with data	Data not remembered for transfer	4A
	Data transferred incorrectly	4A
3.1 Prediction using model	Unable to predict - cannot run model	4A
	Incorrect prediction 1. Does not understand model	4A
	Incorrect prediction 2. Premature conclusions	3B, 4A, 4B, 4C, 4D, 4E, 4F
4.1 Choice of action	No action chosen	4A, 4C
	Incorrect action chosen	4A, 4C, 4D, 4E, 4F
4.2 Use of feedback	No feedback obtained	4B, 5B
	Feedback delayed	5C
	Feedback misinterpreted	5A

7. HUMAN TRUST IN AUTOMATED SYSTEMS

Human trust in automated systems and in particular in computer-based decision aids is a relatively new topic and one that has not received the benefit of extensive research. There are many issues to examine in the human-computer relationship that bear on the degree of trust and also the dynamics of trust that may exist at any point in a sequence of transactions. Much of the work to date has not examined in particular the notion of trust in the framework or context of IW and a general situation where the degree of integrity of any of the information processed by the computer may be suspect. Any sense of mistrust or distrust in these past works comes from the fact that the computer-based processing is embodied in the software created by another human, and in that sense the computer is a "virtual person." Hence, one frequently-cited paper (Muir, 1987) starts with an examination of notions of trust in interpersonal relationships. This is not to say that the insights provided by past research are not applicable or interesting but that they have not considered the special case of hostile penetration of the internal processing on the computer side of the interface.

What is important in any case, *i.e.*, in the establishment of trust in whatever framework or driven by any of a number of factors, is the resultant impacts on patterns of use of the decision aid (which was presumably designed to be beneficial), and, moreover, the combined performance and effectiveness of the human working in concert with the computer/decision aid. As Muir also points out, trust is not a static state in a relationship; it has dynamics and, in many cases, the relationship frequently ebbs and flows from trust to distrust and back again. Additionally, and importantly, it should be understood that people can also trust a decision aid more than is warranted, leading to an unwarranted state of complacency.

7.1 Basic Notions of Trust

The psychological literature points out a number of aspects of the notion of trust in interpersonal relationships:

- it frequently relates to expectations and future events
- it always has a referent, a particular person, thing, or say a specific decision aid or a component of a decision aid
- trust may relate to any or several of the features of the referent, such as
  - reliability
  - accuracy
  - other

While these are helpful, Muir considers them imprecise and cites a definition by Barber (Barber, 1983) as more pointed and as explicitly recognizing the multidimensional nature of a trusting relationship. Barber defines trust in the context of a set of expectations:

1. an expectation of the persistence of "natural and moral orders" in the relationship

2. an expectation of technically competent role performance from the "partner"
3. an expectation that partners in the interaction will carry out their fiduciary obligations and responsibilities

There are, we submit, varying degrees of possible perturbations and violations of these definitional components in the case where Information Operations by a hostile may be occurring; *e.g.*:

Item 1. above implies in essence an assumption of rational behavior, which, in fact, may not be valid in an IW environment; the (corrupted information in a) decision aid may result in irrational behavior or recommendations by the decision aid in certain, perhaps unpredictable, circumstances

Item 2. above implies technical competence, and decision aid technical performance may be compromised by corrupted information

Item 3. above implies responsible behavior and a notion of good faith in the motives of the (decision aid) partner; this is probably correct, by and large, (so long as the IW attack is not "massive") but occasional and irregular responses violating this characterization could occur in a compromised decision aid.

Muir focuses on Barber's "technical competence" component as being at the heart of the trust issue between humans and computers. Barber goes on to expand this component into 3 types of technical competence:

1. expert knowledge
2. technical facility
3. everyday routine performance

and asserts that the levels of performance and expectation from a decision aid might be categorized by this structure. This, or some equivalent taxonomy of expertise, actually applies on both sides of the HCI: we can have situations where expert humans are interacting with decision aids performing routine work, and vice versa. In those cases where the knowledge in the decision aid is beyond that of the human, the human is forced to rely on the assumption of "fiduciary responsibility" since he has no foundation for assessing competence. These situations are helped by the decision aid incorporating a so-called "explanation facility" but this, too, could be presented at levels of sophistication beyond the user's ability. These factors imply a rule that says that the more "prosthetic" the aid is, the more it needs to communicate its intent, direction, understanding of goals, etc.

Continuing to follow Muir, the notion of trust can perhaps be quantitatively expressed—*e.g.*, as a basis for human-in-the-loop experiments—in the sense of its influencing "Factors" as:

$$T = Bo + B1X1 + B2X2 + B3X3 + B4X1X2 + B5X1X3 + B6X2X3 + B7X1X2X3$$

where the B's are parameters, and X1 = Persistence, X2 = technical competence, and X3 = fiduciary responsibility factors.

7.2 Dynamics of Trust

In reference to the dynamics of trust in a relationship, Rempel et al. (Rempel, Holmes, & Zanna, 1985) argue that in the early phases of familiarization between the two "actors" trust depends on consistency of recurrent behaviors under relatively similar conditions—*i.e.*, implying some sense of "repeatability." This will not be perfect however and so the person must develop some sense of acceptable variance in recurrent behavior. The problem in this situation is that humans tend to over-value the behavior in small samples—this itself leads to under-estimation of what the true (or reasonable values of) variance should be. This can lead to a pathological loop—where initial trust leads to an aggravated tendency to value (very) small sample behavior, etc. There is the possibility that (conditioned on the assumption of beneficial intent) as a result, knowledge about a decision aid's behavior and competence will be inversely related to trust: the less we know about the aid, the more we trust it! Other possible trust dynamics can be implied: the more constrained the possible output of the aid, the more predictable it should be, so that trust can be gauged to be inversely related to "degrees of freedom" of the aid. This applies, too, to the nature of the domain dynamics; the less complex and stochastic they are (inherently), the more predictable that aid should be, and so, trust should be directly related to the "stability" of the domain environment. IW effects on these assertions can lead to a number of modifications: *e.g.*, IW effects can alter the nature of the true vs. observed variance in decision aid behavior, and can, therefore, reduce operator levels of trust in what should otherwise be good decision aid performance. This can also lead to increased operator intervention and workload, etc., and IW effects can be thought of as an "intermittent" failure or a "transient" in the behavior of a decision aid. So, IW factors can lead to a variety of degrading effects in the perceived behavior of a decision aid—and it is perceived behavior that counts. But this also implies that operators should be given good training on the aid (in an uncorrupted environment) so that they can also develop insights into, and be alert to possible IW-based corrupting effects—*i.e.*, so they can detect probable IW effects. Of course, system designers should ideally design some type of intrusion detection methods for IW-based penetration as well.

Later in a relationship, trust dynamics depend on the aid's behavior history, particularly under conditions of risk or stress. If the aid's cumulative history is considered "good," high trust will evolve. This means too that the aid must be given chance to fail or to encounter the high-risk/high-stress problems; if the human always overrides the aid in those cases, no data will be available from which to gauge trust. However, decision aids that have a high false alarm rate will eventually tend to be disregarded; of course, when an alarm is real, such failure to heed them can be catastrophic. The balance seems to be between a system that requires frequent nurturing and attention and one in which the operator can remain quite passive. Humans are known to be poor at monitoring tasks and some design advice says to involve the human as a "performer" rather than "observer," presuming a balanced workload also results. In those cases, the interactive nature of the human-computer pair should also result in a more insightful basis for trust. Another factor here is the underlying, inherent nature of the complexity of the domain problem. There is a tendency by humans to ascribe failure to lack of ability rather than to

extreme complexity in the domain, so the competence limits of the aid and the complexity of the domain both need to be well understood by the user so that correct levels of trust can evolve.

The behavior of an aid in the face of chronic errors seems to be able to be overcome by human intervention; however, such repetitive failure brings down the general level of trust in the aid. Lee and Moray's study (Lee & Moray, 1992) shows that this loss of trust occurs somewhat slowly, and that there is a "hysteresis loop" (our term) in trust dynamics—they use the term "inertia." They look at both a linear regression-based trust model and a time-series based model to help account for the dynamics. They argue that a proper model would include a causal component and a dynamic component. Lee and Moray develop an autoregressive moving average vector form of a dynamic trust model that fit the data of their experiments very well. As regards transient errors by an aid, these cause a drop in both man and machine performance and a loss of trust that, again, takes time to be re-established.

7.3 Distrust and Mistrust

The notion or state of Distrust exists when the aid is considered to be operating beyond its judged boundaries of technical competence. The notion or state of Mistrust exists when the human accords an incorrect level of trust to the aid, *i.e.*, when a competent aid is distrusted or when an incompetent one is trusted. These are conditions of error in the fashion of "Type I and Type II" errors in hypothesis testing. Where the Trust/Distrust threshold is set depends in part on notions of consequent risk and cost, and of operator level of skill. "Blind Trust" is not typical in decision-aided environments because users are aware that there must be some level of uncertainty in decision aid performance since the system is designed with a human in the loop to begin with (else why is the human there?). These factors lead to both design-level and operational-level questions of functional allocation. The designers will have one view of the man-machine functional boundary but patterns of use may reveal that users see that boundary in another way.

7.4 Dealing with Complex Application Environments

When a decision aid is employed in a complex domain, the issue of trust can be somewhat masked by the complexity in that the human, unless they have exceptional insight to the problem and what should be "good" aid recommendations, may never know the level of correctness the aid is working at and the integrity of its recommendations. Experiments have been run in such environments where seeded errors were inserted into the decision aid, and human operators accepted the results and exhibited high confidence in the tool.

7.5 Riley's Model

Riley (1989) suggested that the operator's decision to rely on automation may not depend only on the operator's trust in the system but rather on a more complex relationship among trust, self-confidence, and a number of other factors. One major thrust of this model is that if the operator were very self-confident, that he would tend to do the work manually, but that

this relationship is mediated by other factors such as workload and level of risk involved. This model is shown below in Figure 7.5-1:

Arrows represent influences between factors. The "reliance" factor represents the probability that an operator will use automation and is influenced by self-confidence and trust. Trust, in turn, is influenced by actual reliability of the aid and a duration factor meant to account for increasing stability of the operator's opinion of the aid with use. Some have remarked that this model is more appropriate to group-wise employment of decision aids/automation and that individual users would employ much simpler strategies influenced by a smaller number of factors.

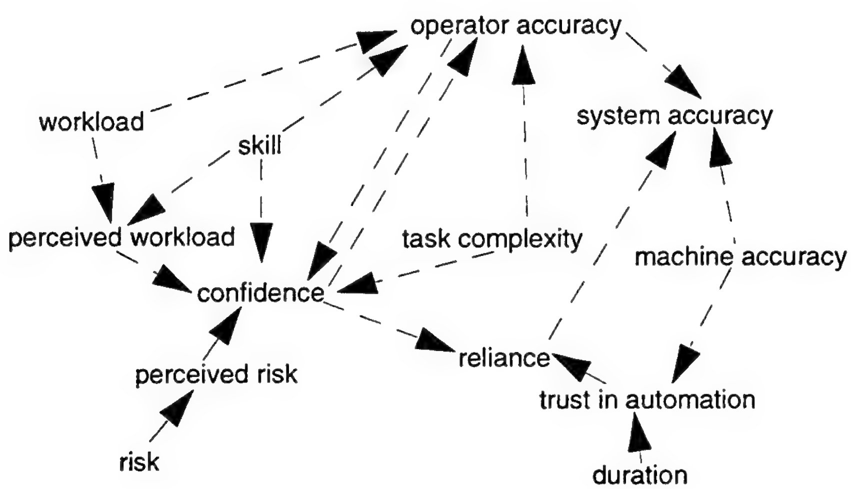


Figure 7.5-1 An Initial Theory of Operator Reliance on Automation
(Arrows Indicate the Hypothesized Directions of Influence.)

However, experiments run by Riley suggest an even more complex model for behaviors across a group as shown in Figure 7.5-2:

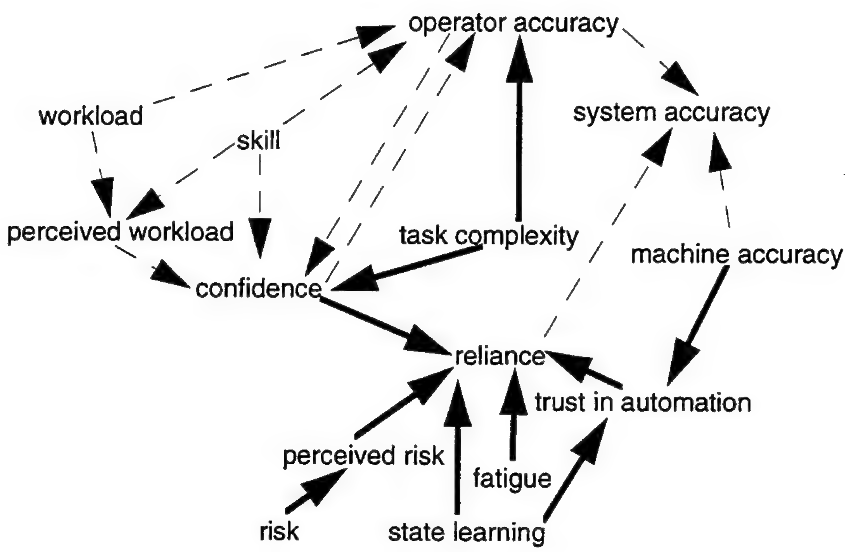


Figure 7.5-2 The Revised Theory of Automation Use
(Dotted arrows show hypothesized relationships that have not been confirmed by experimental evidence, whereas solid lines represent those relationships supported by evidence from these studies.)

The dashed lines show relationships that were not corroborated by his data, and the solid lines show relationships that were corroborated by his data. Fatigue and learning about system states now replace the duration factor of Figure 7.5-1. It is known, for example, that in monitoring tasks automation can induce complacency in operator interaction. Learning is also shown to influence trust directly.

8. CULTURAL EFFECTS ON ADVERSARIAL DECISION-MAKING

No specific works in the area of cultural effects on decision making or especially adversarial decision making were located in our literature search efforts. However, we found what we believe to be reasonably related works in the management literature having to do with issues in multinational corporations and their various functions and operations. These inputs range from definitions of what culture is to the notions of different societal values and beliefs, recognition factors for decision makers and some other related topics. Even these works however do not address directly the impact of these factors explicitly on decision making. As a first-cut input addressing this topic for our purposes, we have simply collated and assembled some inputs from the cited references. This subject will be explored further in the next phase of work.

8.1 Basic Notions of Culture

8.1.1 What Culture Is (Hoecklin, 1995)

(1) *A Shared System of Meanings.* Culture dictates what groups of people pay attention to. It guides how the world is perceived, how the self is experienced and how life itself is organized. Individuals of a group share patterns that enable them to see the same things in the same way and this holds them together. Each person carries within him or herself learned ways of finding meaning in his or her experiences. In order for effective, stable and meaningful interaction to occur, people must have a shared system of meaning. There must be some common ways of understanding events and behavior, and ways of anticipating how other people in one's social group are likely to behave. For example, waving a hand or planting a kiss has no clear meaning without the context being understood. Furthermore, the intended meaning of a gesture need not coincide with the perceived meaning except where cultural identities match. It is only when the meanings do coincide that effective communication can happen.

(2) *It is Relative.* There is no cultural absolute. People in different cultures perceive the world differently and have different ways of doing things, and there is no set standard for considering one group intrinsically superior or inferior to any other. Each national culture is relative to other cultures' perceptions of the world and doing things.

(3) *It is Learned.* Culture is derived from one's social environment, not from one's genetic make-up.

(4) *It is About Groups.* Culture is a collective phenomenon that is about shared values and meanings.

The noted business author and scholar Geert Hofstede describes culture as the "collective programming of the mind" and explains that it lies between human nature on one side and individual personality on the other (see Hoecklin, 1995). Figure 8.1.1-1 shows his model of three levels of uniqueness in human mental programming.

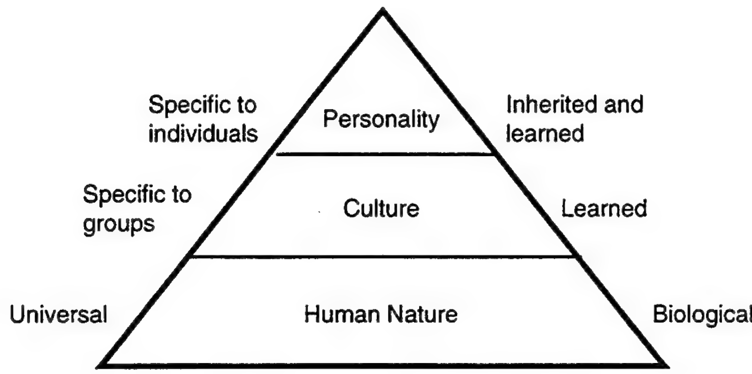


Figure 8.1.1-1 Hofstede's Three Levels of Human Mental Programming.

In Hoecklin (1995), a collection of definitions of Culture by a number of experts is assembled; these are shown below in Figure 8.1.1-2:

Figure 8.1.1-2 Concepts of Culture by a Set of Experts (Hoecklin, 1995)

Tylor E. (1871). That complex whole which includes knowledge, beliefs, art, morals, laws, customs and any other capabilities and habits acquired by man as a member of society.
Herskovits M.J. (1948). The man-made part of the human environment.
Kroeber A. L. and Kluckhohn C. (1952). Transmitted patterns of values, ideas and other symbolic systems that shape behavior.
Becker and Geer (1970). Set of common understandings expressed in language.
ran Maanen J. and Scirein E. H. (1979). Values, beliefs and expectations that members come to share.
Schwartz M. C and Jordon D. K. (1980). Pattern of beliefs and expectations shared by members that produce norms shaping behavior.
Hofstede G.H. (1980). The collective programming of the mind which distinguishes the members of one human group from another.
Louis M.R. (1983). Three aspects: (1) some content (meaning and interpretation) (2) peculiar to (3) a group.
Hau E. T and Hall M.R. (1987). Primarily a system for creating, sending storing and processing information.
Harris PR. and Moran R.T (1987). A distinctly human capacity for adapting to circumstances and transmitting this coping skill and knowledge to subsequent generations.

8.1.2 What Culture Is Not

(1) *Right or wrong.*

(2) *Inherited.*

(3) *About individual behavior.* There are wide variations in individual values and behavior within each national culture.

8.1.3 Different Layers of Culture

Each person carries around several layers of cultural "programming." It starts when a child learns basic values: what is right and wrong, good and bad, logical and illogical, beautiful and ugly. Culture is about one's fundamental assumptions of what it is to be a person and how one should behave.

8.1.4 Images of Cultures

Self-image, or how we see ourselves, is a way of expressing our cultural identity. Cultural self-image tells us who we think we are and how we can distinguish "us" from "them." By asking someone from a culture what it means to be an American, Japanese, or Arab, a list of cultural characteristics emerges that gives us a good description of what that particular culture values and how it sees itself in relation to other cultures.

Of course, how we see ourselves is not the same thing as how others see us. What we see as natural, normal, and even ideal, other cultures see as different. To the extent that "your cultural values overlap with mine, your image of my culture will be positive. To the extent that our values differ or conflict, your image of my culture will be negative."

8.2 Notions of Values Across Cultures

8.2.1 American, Japanese, and Arab Distinctions

One attempt to explain the differences in cultural value contrasts more clearly is developed in Table 8.2-1 (Elashmawi & Harris, 1993), which compares specific contrasting values of American, Japanese, and Arab cultures. Reading across the table from left to right provides perspective on the values of each culture.

In examining Table 8.1, we note that one of the top American values listed is freedom—freedom to choose one's own destiny—whether it leads to success or failure. Japanese culture, on the other hand, finds a higher value in belonging. In this culture, one must belong to and support a group(s) to survive. Belonging to a group is more important to Japanese culture than individualism. Arab culture is less concerned with individualism or belonging to a group, concentrating instead on maintaining family security and relying on God for destiny. Individual identity is usually based on the background and position of the person's family.

The value American culture places on independence and individual freedom of choice naturally leads to the idea that everyone is equal regardless of age, social status, or authority. Japanese and Arab cultures, however, place more value on age and seniority. The Japanese individual will always give way to the feelings of the group, while Arabs respect authority and admire seniority and status.

In most business situations, Americans would come with a competitive attitude. The Japanese, conversely, value group cooperation in the pursuit of success. An Arab will make compromises in order to achieve a shared goal between two parties. One might think of the opposites of these value-based behaviors as regards the adversarial case.

Table 8.2-1 Cultural Contrasts in Value

Americans	Japanese	Arabs
1. Freedom	1. Belonging	1. Family security
2. Independence	2. Group harmony	2. Family harmony
3. Self-reliance	3. Collectiveness	3. Parental guidance
4. Equality	4. Age/Seniority	4. Age
5. Individualism	5. Group consensus	5. Authority
6. Competition	6. Cooperation	6. Compromise
7. Efficiency	7. Quality	7. Devotion
8. Time	8. Patience	8. Very patient
9. Directness	9. Indirectness	9. Indirectness
10. Openness	10. Go-between	10. Hospitality
11. Aggressiveness	11. Interpersonal	11. Friendship
12. Informality	12. Hierarchy	12. Formal/ Admiration
13. Future-orientation	13. Continuation	13. Past and present
14. Risk-taking	14. Conservative	14. Religious belief
15. Creativity	15. Information	15. Tradition
16. Self-accomplishment	16. Group achievement	16. Social recognition
17. Winning	17. Success	17. Reputation
18. Money	18. Relationship	18. Friendship
19. Material possessions	19. Harmony with nature	19. Belonging
20. Privacy	20. Networking	20. Family network

8.2.2 Influences on Behavior of Value and Belief Differences

We should point out that the problem of cultural clash stems from both the differences and priority of each value in the set. In order to assess value diversity, the management texts say one should try first to identify one's own set of cultural values, then those of the country and person with whom one is dealing. One should also recognize that these values and priorities are merely different, not right or wrong. People tend to see anything that is different from their culture as wrong. Each culture has certain agreed-upon values, and the individual is rewarded for

adherence or punished for failure to adhere to them. Members learn to do so in order to survive, coexist, and succeed in that culture.

In American culture, the phrase "time is money" is commonly accepted as a framework for the desire to finish a task in the shortest amount of time with the greatest profit. If a process is considered inefficient, it "wastes" time and money, and possibly will be abandoned. The Japanese, however, value high quality over immediate gain, and they patiently wait for the best possible result. Arab culture also values quality more than immediacy, but the trust in the business relationship is the most important value.

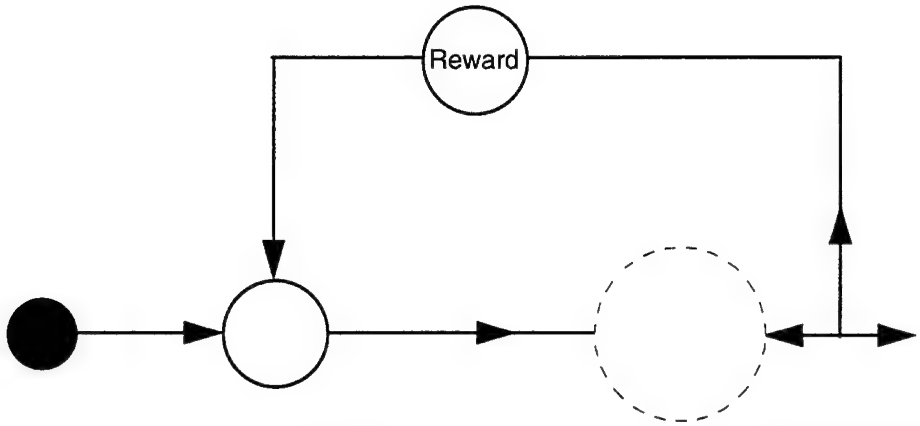
Americans emphasize individual achievement and are result-oriented; therefore, they value directness and openness when dealing with others, enabling individuals to finish tasks more quickly. Because of the values of directness and equality, Americans tend to be informal when speaking and writing, often addressing each other by first names. The Japanese prefer to follow an indirect, harmonious style when dealing with others. Go-betweens help to move the process along, and interpersonal harmony is considered more important than confrontation. The Arab culture, like the Japanese, avoids direct confrontation. However, Arabs prefer to negotiate directly in the spirit of hospitality and friendship until a compromise is reached.

Americans tend to be oriented toward the present and immediate which explains why Americans value taking risks. To an American, accomplishing a task as quickly as possible brings the future closer. The Japanese, however, view time as a continuum, and are long-term oriented. As a result of their value of a long-term, quality-based relationship, the Japanese tend to be conservative and patient. The Arab culture believes that the present is a continuation of the past and that whatever happens in the future is due to fate and the will of God.

A principal value of American culture is individual achievement. When someone accomplishes something by him or herself, he or she expects and receives recognition for being a creative person, or the one who developed the best idea. The Japanese, because of their value of group achievement, seek information in order to help the entire group succeed. In Arab culture, the individual is not as important as preserving tradition. An Arab measures success by social recognition, status, honor, and reputation.

A successful culturally competent person must be aware of his or her own priorities, as well as those of his or her country or society, and reorganize them properly to achieve group success. That person must also make an attempt, in initial dealings with the other culture, to adhere to and respect the other system. Once the person is accepted by the group, then that person can slowly introduce his or her own set of values to the group. If both sides recognize the new values as necessary for coexistence, then the values will be accepted, and cultural synergy will occur naturally.

Figure 8.2.2-1 proposes that all of our behaviors in business or social life are influenced by both our belief systems (such as life, death, religion, and nature) and our reward values. These beliefs are taken by human beings as accepted norms, and it takes a major crisis to change them.



BELIEFS	VALUES	COMMUNICATIONS
Life/death	Competition	Social organization
Nature	Independence	Nonverbal communication
History	Directness	Emotional response
Religion	Risk-taking	Aesthetics
		Food
	Group harmony	Activities orientation
	Cooperation	
	Age-seniority	
	Information	
	Devotion	
	Interrelationship	
	Family harmony	
	Formality/status	

Figure 8.2.2-1 The Belief, Values, and Communications Model

8.2.3 Behavioral Factors in Decision Making

8.2.3.1 Rewards:

Our set of values change according to the group or societal system of rewards and punishment. In the American system, for example, the values of independence, competition, and risk-taking are rewarded, enhanced, and encouraged by the group. If an executive working in the United States tries to introduce group harmony, seniority, and status as prime values for his business success, he will probably be discouraged and be forced to comply with the more valued system of American independence, openness, directness, and risk-taking.

By contrast, many of the Japanese reward systems are based on group harmony, group consensus, and group achievement. If a Japanese executive were to attempt to introduce self-

reliance, individual competition, and risk-taking into the Japanese work environment he would more than likely be disparaged within his culture.

The material rewards that are culturally appropriate reflect the values of the macroculture. Americans measure individual success more in material possessions than in social status or family/class membership. Monetary rewards motivate Americans. Increased salary, commission, or participation in a profit-sharing plan are methods used to recognize individual efforts. Many American entrepreneurial technology companies motivate new employees by offering them company stock rather than high salaries. Rewards, like recognition, can take many forms—from a company car, to a promotion, to a desirable transfer.

The Japanese are motivated by rewards shared among the group, such as bonuses, social services, and fringe benefits available to group members. Acknowledging the achievement of an individual member of the group is inappropriate. Recently, many Japanese companies have begun rewarding their employees with memberships to health or golf clubs for their efforts.

Arabs are motivated by gifts for the individual and family that reflect admiration or appreciation for the individual's achievement. A one- or two-day salary bonus is a good motivator for Arab workers who, for example, exceed their normal efforts. Giving such bonuses to individuals is used as a motivational tool for others. In small business environments, an Arab business owner might send a good worker a gift in the form of a household appliance that he or she can enjoy with his or her family.

8.2.3.2 Motivation: All people are motivated by the power of feeling in control of their own work space. Americans feel good about being independent and in control of their own destinies—a direct reflection of values, which include control over decision making, time, and reward. Because Americans value privacy, self-reliance, and individualism, they are motivated to control their own decisions, even if this control involves considerable risk-taking.

On the other hand, Japanese motivation comes through group harmony and consensus. The individual feels in control when he or she is in harmony with the group; it is the greatest source of individual motivation. Maintaining harmony between different sections and departments is a particularly important task of upper level management A top manager in Japan will not approve a decision unless all departments have agreed on its implementation. Of course, each department will have already gone through a similar internal consensus process, in which all of its members participated.

The Arab manager strives for control and motivation of others through a parenting relationship. Everyone tries to be in the position of the manager (parent) in order to gain respect and responsibility. Title and status play a major role in rewarding individual achievement. Contrast the Arab model with the Japanese model, in which age, seniority, and experience are all respected when making major decisions.

We can see that in a multicultural work environment, not everyone is motivated by the same factors. Motivational processes, tools, and values reflect our culture, directly or indirectly.

The motivation process—how it's controlled, who it appeals to, how to recognize it, and how to reward or punish employee behavior—is directly related to cultural values.

Table 8.2.3.2-1 shows some of the motivational tools and cultural factors for our three distinct cultures, American, Japanese, and Arab.

Table 8.2.3.2-1 Cultural Contrasts in Motivation

	American	Japanese	Arab
Management Style	Leadership; Friendliness	Persuasion; Functional group activities	Coaching; Personal attention; Parenthood
Control	Independence; Decision-making; Space; Time; Money	Group harmony	Of others/ parenthood
Emotional Appeal	Opportunity	Group participation; Company success	Religion; Nationalistic; Admiration
Recognition	Individual contribution	Group identity; Belonging to group	Individual status; Class/society; Promotion
Material Awards	Salary; Commission; Profit-sharing	Annual bonus; Social services; Fringe benefits	Gifts self/family; Family affair; Salary increase
Threats	Loss of job	Out of group	Demotion; Reputation
Cultural Values	Competition; Risk-taking; Material possession; Freedom	Group harmony; Achievement; Belonging	Reputation; Family security; Religion; Social status

Management styles are also important and can be effective motivators in each culture. Americans react positively to a leadership style characterized by professionalism and friendliness. However, American managers separate personal and business matters. An employee who has a personal friendship with the manager may be surprised when the manager tells that same employee that he or she is not performing up to expectations on the job. Most American managers move up the corporate ladder by being self-motivated, willing to take risks, competitive, and success-oriented. Naturally, these managers use these similar qualities to lead and motivate others in career development.

Japanese managers also motivate employees through continuous counsel and persuasion. They maintain group harmony through involvement in the professional and personal lives of their staff. Employees expect their managers to develop their career paths, as well as to

guide them in major activities. Older or retired executives often assume a mentoring role with younger managers and become strong, motivational influences.

The Arab manager will be most effective in a parenting-type role that includes coaching and personal attention. The manager's status and authority level, and his ability to punish or reward the employee allow him to assume this role. At the same time, managers separate the working relationship from personal matters so as not to lose their authority and control over their employees.

As discussed, it is very clear that motivational tools and processes reflect each unique culture. In the American culture, competition, risk-taking, material possessions, self-reliance, and freedom are all motivational values. In contrast, group harmony, belonging, and achievement are important and valued tools in motivation of Japanese employees. Arab workers value reputation, authority, and social status; and respond to these values in their motivation process. Each organizational culture responds to appropriate and relevant motivational patterns within the larger culture's established values. What motivates *you* within *your* culture is not necessarily what motivates someone from another culture. Recognizing this simple fact is essential when working to motivate employees of diverse cultural backgrounds.

8.2.3.3 Emotional Appeal: Americans respond to available opportunity. Because the culture values risk-taking and is very time-conscious, Americans look at the configuration of resources at any given time as presenting unique opportunities. Americans often use the analogy of a "window of opportunity"—an opening to be used or lost. An American marketing manager will be motivated to open an overseas office if he or she believes a competitor is planning to enter that market. The motivation to take the risk in a new market comes from the desire to seize the opportunity. Likewise, American business is filled with sports analogies and terminology, such as, "win the game at all costs," or "you have to be a team player."

The Japanese are motivated by reputation and company success, which are allied with their cultural values of belonging and group achievement. A Japanese manager will feel he has to accept an overseas assignment in order to assure the company's success. Regardless of the disruption that such an assignment may cause to his personal life, the Japanese manager will not risk embarrassment by refusing the boss's request on behalf of the company's interest. The company's success and harmony within the group may take priority over the manager's immediate family requirements.

Arab motivation comes from an appeal to the sense of self within the authority structure. A manager will accept an overseas assignment if it results in personal gain in position, status, and money. Appeals to religious values may also be strong motivators in times of crisis or celebration. Words of admiration and flattery for individual achievement are also motivational.

8.2.3.4 Recognition: Americans want to be directly recognized for their individual contributions and achievements. When a group project is successful, the group manager will expect recognition and reward for the achievement This recognition may come in the form of a bonus, a salary increase, or a promotion to a position of higher responsibility. In turn, the

manager will individually recognize the contributions of the team members during their performance appraisals.

Japanese recognition comes through identification with the group in ever-widening circles: family, working group/team, department, division, company, and nation. Recognition for group achievement belongs to the group rather than to individuals.

Recognition in Arab cultures generally results from the individual's status in the hierarchy. When a department reaches its goal, the recognition will go to the department manager who will then recognize the next level under him. The ripple effect will continue until it reaches the lowest level employees.

8.2.3.5 Threats: The opposite of a reward is a punishment. The effectiveness of a punishment in the form of a threat as a motivational tool depends upon the cultural values of the individual. Since Americans' identities are often directly linked to their jobs, the threat of being fired is significant. However, since American society is highly mobile, Americans may react to the threat of being fired by quitting. Americans may not be as concerned as Japanese or Arabs who may lose their jobs in this situation.

To the Japanese, the greatest threat is formal or informal exclusion from the group. If an individual is not contributing to the group's functional output due to personal ideology that differs from the group's, the manager's task is to counsel that individual before he or she feels pressure from the group. Many Japanese complain that they cannot take full advantage of their vacation days. The Japanese feel that if they are away from the office for more than a few days, the other workers will treat them as if they had abandoned the group. Although a Japanese company rarely fires an employee, group pressure may force an individual to resign or ask for a transfer.

To the Arab, a demotion is a threat to one's reputation and status. If such action is necessary, it has to go through a lengthy review procedure to ensure that the action is justified to give the employee ample time to correct his performance. Loss of a job is a deep embarrassment to the employee, his colleagues, and family, and will be difficult to remedy.

8.3 Intercultural Negotiations

Intercultural negotiation consists of three major processes:

- Establishing rapport
- Exchanging information
- Persuading

Our cultural values influence all aspects of our behavior in business matters. Throughout this section, we will focus on the process of intercultural (not necessarily international) negotiations. We will identify the general process that people and companies go through in establishing a relationship or negotiating an exchange of products/services.

While negotiating with others, keep in mind your own cultural values and those of other cultures that have been discussed herein. In recognizing how such cultural values influence everyone's behavior, you will be more sensitive to their needs, and will negotiate with understanding.

Table 8.3-1 presents important components in the negotiation processes. In this table, we present the cultural contrasts among Americans, Japanese, and Arabs. Important elements presented include group compositions, the number of people involved, space orientations, and other elements as shown in the table.

Table 8.3-1 Contrasts in Intercultural Negotiations

	Americans	Japanese	Arabs
Group Composition	Marketing oriented	Function oriented	Committee of specialists
Number Involved	2-3	4-7	4-6
Space Orientation	Confrontational; Competitive	Display harmonious relationship	Status
Establishing Rapport	Short period; Direct to task	Longer period; Until harmony is established	Long period; Until trusted
Exchange of Information	Documented; Step-by-step; Multimedia	Extensive; Concentrate on receiving side	Less emphasis on technology, more on relationship
Persuasion Tools	Time pressure; Loss of opportunity; Saving/making money	Maintain relationship references; Intergroup connections	Go-between; Hospitality
Use of Language	Open/direct; Sense of urgency	Indirect; Appreciative; Cooperative	Flattery; Emotional; Religious
First Offer	Fair +/- 5 to 10%	+/- 10 to 20%	+/- 20 to 50%
Second Offer	Add to package; Sweeten the deal	-5%	-10%
Final Offer	Total package	Makes no further concessions	-25%
Decision Making Process	Top management team	Collective	Team makes recommendation
Decision Maker	Top management team	Middle line with team consensus	Senior manager
Risk-taking	Calculated; Personal; Responsibility	Low group Responsibility	Religion-based

9. THE GAME THEORETIC PERSPECTIVE

This section will discuss the role of Game Theory and related topics to the analysis of information warfare problems. We use the term *information warfare* to characterize one extreme of a range of problems. These problems involve the use of information transfer to maximize objectives among cooperative and non-cooperative senders and receivers. These can vary from the exchange of collaborative intelligence to information warfare.

9.1 About Game Theory

Game theory involves the study of mathematical models of systems composed of interacting, independent decision makers (Basar & Olsder 1982, Meyerson 1991, Owen 1982). Such models can help analyze the behavior and performance of these systems under conditions of conflict or cooperation or both.

Since the advent of linear programming and game theory in the 1940's and early 1950's (see Dantzig, 1963 and von Neumann & Morgenstern, 1947), a substantial effort has been directed toward analyzing the behavior of interacting decision makers. In these models, each decision maker attempts to optimize his or her objectives in view of decisions made by others. The earliest work in game theory of von Neumann & Morgenstern (1947) and Nash (1951) addresses many important aspects of these problems. Dantzig and Wolfe (1960) and Baumol and Fabian (1964) developed the Decomposition Principle for linear programming. With this early technique, mathematical programming models were developed to describe the behavior of independent individuals interacting within network structures. Within these networks, the decision makers directed the flow of resources, costs, and information.

The term "game theory" is somewhat unfortunate in that it often appears limited to the study of parlor games. Game theory and the field of *optimal control theory* are closely related. Both approaches model economic and political conflicts, worst case designs, and war games (Basar & Olsder 1982). All of these models share a common theme. Each individual decision maker (commonly called a *player*) attempts to establish a strategy to maximize his or her own benefits. In addition, each player also considers the decision making strategies of other players.

The field of game theory is often divided into *cooperative* and *non-cooperative* games. In non-cooperative game theory models, the players are mutually independent, never sharing resources, and never relinquishing autonomy. Cooperative game theory models allow players to form coalitions combining resources, decision making, and proceeds.

Game theoretic models are also classified as *dynamic* or *static*. With *dynamic games* the sequence of decisions are important, while in *static games*, they are not. Dynamic game models often appear more appropriate for those problems that involve time-dependent decisions. However, in some cases, static models can provide valuable insight. This is true, for instance, in cases where information exchange and events take place at very high speeds.

Game theory and optimal control theory have a great deal in common with other constrained optimization problems. The relationships between these two fields are categorized in Table 9.1-1 (from Basar & Olsder 1982):

Table 9.1-1 Constrained Optimization Problems

	One Player	n-Player
Static	Mathematical programming	(Static) Game theory
Dynamic	Optimal control theory	Dynamic game theory

Game theory can also be characterized as *multi-person decision theory.* It also shares many concepts with the field of *statistical decision theory* (see, for example, Ferguson 1967). There is one key difference. In game theory models, the opponent maximizes his or her own objective. In statistical decision theory, the other player is not an active opponent, but rather an impartial participant who establishes a state of nature for the decision maker.

In addition, there is a key distinction between multi-person game theoretic models and multi-criterion's optimization models. As mentioned earlier, game theory deals with individuals who may act independently, and with conflicting objectives. Multi-criteria decision models are used to solve problems involving the conflicting objectives of one planer, or a harmonious bevy of planners.

9.2 Game Theory Issues in Information Warfare

Information plays an important role in game theory models. The players act autonomously. Therefore, the amount and type of information exchanged is often pivotal to the progress of the game.

Most of the information models currently provided by game theory are too simple to apply directly to IW. However, the existing game theoretic approach can provide an excellent framework for basic analysis immediately and further research in the future.

In many applications of IW, the objectives of the transmitter of the information, rather than the information itself, become of paramount importance. The information then becomes a vehicle for maximizing the benefits of the sender. In some cases, the receiver only uses the information to ascertain the objectives of the sender. The problem of the receiver, then, becomes one of determining the objectives of the sender in the shortest period of time.

The diagram in Figure 9.2-1 will serve as the basis for our discussion of two-sided information exchange. For our discussion here, the two players will be called *sender* and *receiver. H*owever, their roles may reverse throughout the progress of the game, as a function of

time. The information transfer is often bi-directional with the *information* sent from the sender to the receiver resulting in a *response* from the receiver to the sender.

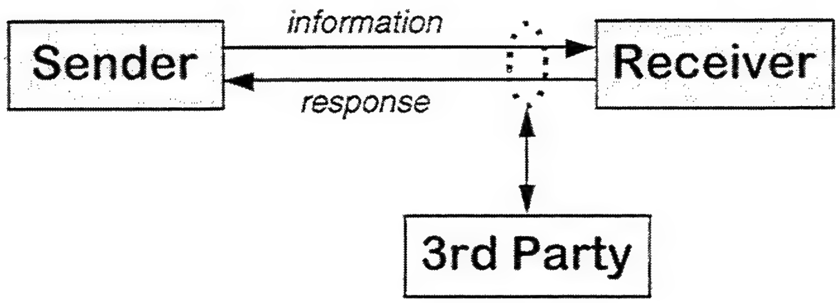


Figure 9.2-1 A Two-Sided Information Model

In section 9.3, we will also briefly consider the addition of a *third party* intercepting the information flow between the sender and receiver. This additional party might be a passive listener or actively interested in the progress of the game. For example an active participant might intercept and deliberately change the information being transferred, while a more passive participant might simply perturb the information with random noise.

9.2.1 A Two-Player Model

First, we will consider the simpler two-sided information exchange model illustrated in Figure 9.2.1-1. Each player selects a strategy from a set of available strategies. A strategy is a rule (that is, function) that specifies a player's actions for any given set of conditions. For example, a strategy might specify that the receiver performs a particular task when receiving a known packet of information. In addition, the receiver may send information back to the sender as a response.

First, we will consider the simpler two-sided information exchange model illustrated in Figure 9.2.1-1. Each player selects a *strategy* from a set of available strategies. A strategy is a rule (that is, *function*) that specifies a player's actions for any given set of conditions. For example, a strategy might specify that the receiver performs a particular task when receiving a known packet of information. In addition, the receiver may send information back to the sender as a *response*.

For the sender...
- information sent to receiver
- action of the receiver
- information response from the receiver

For the receiver...
- information sent by sender
- action of the receiver
- information response to the receiver

Moreover, the information passed between sender and receiver may also change the feasible set of decisions that each player may make. Therefore, each player's actions may affect both the objective function and decision space of the other player. (Bialas and Karwan, 1984)

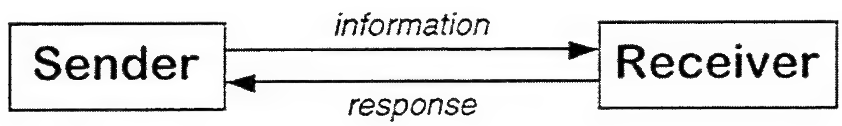


Figure 9.2.1-1 A Simple Two-Sided Model

Several models are already available for analyzing this type of optimization problem. The mathematical foundation of this work rests on the theory of Stackelberg games as a tool for modeling sequential, preemptive optimization problems. The early work was restricted to linear objective functions for each of the players and a requirement that all feasible decisions had to reside within a convex polytope (see Bialas & Karwan, 1984). More recently, many of these results have been extended to problems with generalized objective functions and feasible regions.

One of the key results from Stackelberg game theory is the fact that the optimization problem for the sender can be nonconvex. This is true even if both players' objective functions are linear and the strategy set is a convex polyhedron. Moreover, the joint optimization problem of the sender and the receiver may yield *inadmissible* solutions, even if each of the players chose individually optimal strategies (Bialas & Chew, 1982). In other words, the following scenario is possible: The sender chooses his or her best transmission strategy. The receiver then provides the best response to that information. Yet there are feasible strategies that would result in improvements for *both* players.

The solution can possibly be inadmissible not because of a failure of the model. Instead, it is a representation of what could actually happen in practice. The reason for this behavior is two-fold. First, the decisions must be made sequentially across time and space. This is due to the nature of the information-response process. This prohibits guaranteed coordination of strategies and players' objectives. Second, there is no mechanism (at least in this model) for the transfer of benefits between the players (Willick, 1995). For example, Hunter (1992) has used these principles in the coordination of operating strategies for river systems with several reservoirs.

9.2.2 A Two-Player Model with Information Degradation

Even the simplest model, as discussed in Section 9.2.2, produces a problem that is challenging to solve. In that model, both players know each other's objectives and decision-space with certainty. When uncertainty, deception and information degradation are introduced, the optimization problem for both sender and receiver becomes even more difficult.

The most natural extension of the simple two-player model, is the model illustrated in Figure 9.2-1. In that model, a third individual (perhaps actively participating as a third player)

intercepts and/or manipulates the information between the sender and the receiver. The strategies of the third participant can include

- intercepting and using the information without detection
- changing or augmenting the information and/or response
- adding random noise to the information and/or response
- completely substituting itself as a counterfeit sender
- being an agent of the sender, transmitting deliberately false information on behalf of the sender.

There has been some work on developing solution techniques for games where the objectives are uncertain. As previously mentioned, in many IW problems determining the objectives of the opponent are often more important than the actual processing of the information. In such cases, it is the role of each player to select an optimal information or response strategy to indirectly determine the objectives of the other player. Some related work in this area has been done on optimal determination of response surfaces.

10. CONCLUSIONS AND RECOMMENDATIONS

The study of single-person behavior is itself a challenging task, given the nature of humanity and especially of cognition and the broad range of factors that shape human response to information input. Extending the study framework to the two-sided adversarial case, with each adversary employing different decision aids, and involving the unknowns related to the hostile and covert aspects of adversarial relationships makes the modeling of such interaction quite challenging indeed.

Nevertheless, this report is considered to offer some insights into this problem, and some perspectives that lay a foundation for future work toward deeper understanding of such adversarial relationships in the context of future, information-based warfare. The distinctive aspect of the current project is that it has assembled, excerpted, summarized, and critiqued a body of material on a set of topics that collectively represent many of the key issues that must be investigated to develop a comprehensive understanding of adversarial decision making. On the automation side, information dependencies and vulnerabilities in the DF process that today forms the kernel of decision-aiding tools were examined; this particular viewpoint has not been previously examined. On the human side, human error patterns, human trust in automation, and cultural effects in decision making have been examined. On the "analytical" side, an in-depth assessment and review of informational value in the framework of decision making was carried out, and a game-theoretic viewpoint was also examined.

Much of the focus of current-day IW has been on defensive aspects, and it is those aspects that give each adversary some degree of control of his information environment. But this area will no doubt follow the point-counterpoint legacy of EW and at any moment in time the "Direct IW" situation will be somewhat out of balance for one of the participants. To the extent one adversary can model the other's decision-aiding/data fusion processes, those processes will be subject to some Direct IW attack. Given that most experts consider that perfect security is impossible, the issue of Trust in Automation will also arise and the evidence to date is not encouraging; humans do not exhibit much tolerance for failure of automated processes. The degree of severity or criticality of this imbalance to each participant depends then on specifically what information has been corrupted—this leads to the issue of informational value in decision making, and is why this study and report spent considerable time and effort on this subject. The challenge here in the sense of modeling such decision making environments is whether the models created are generic or not, *i.e.*, whether the nature of information dependencies in adversarial decision making can be extended across problem domains and problem parameters. In a way, this is a "reuse" question: whether the modeled dependencies of decision making on information types can be abstracted, generalized, and reused for various problems.

On the other hand, the "Indirect IW" aspects are (more or less) completely non-controllable by each adversary. It is true that each can influence the other's range of behavioral mobility through smart, constraining tactical operations, but, by and large, each operates autonomously in a behavioral sense. This means that the conduct and achievement of perception

management and its effect on the other's information environment is generally less controllable than for Direct IW. But this aspect too depends on each participant's insight into the other's possible behavior patterns, and, also, on the degree of imbalance that may exist in each's surveillance capabilities. So here, too, the question is: what don't I know or what is likely to be the result of deception, and is it important to me? Again, this means that the dependencies and notions of value of specific elements of information are the critical aspect. The question is not whether the integrity of any piece of information is suspect (because some will be corrupted); it is whether the integrity of specific, important elements of information have been corrupted.

There is one other important factor in all this: it is the balance of automated vs. human-based functionality allocated in the course of system design. The view taken here is that current-day trends toward ever-increasing reliance on automated processes will continue and that the role of automated decision-aiding and DF processes will increase in the future. The assertion is that the overall dependency of humans on automation, and the role of automated processing in future IW/decision making environments will be significant, if not major. This implies that the focus of analysis as regards informational value should be in the context of how the automated processes support decision making, *i.e.*, what the critical informational elements are in the automated processing. This is not the focus to the exclusion of assessing human-based decision making dependencies on information, but is a question of degree. The specific tie-in on the human side is the notion of trust. That is, if these assertions are reasonable, they portray future situations where humans will depend on ever more automated processes; this begs two questions:

1. Where are the critical dependencies and vulnerabilities in the automated processes?
2. In spite of (1), what will be the patterns of trust of humans in automation when the humans depend greatly on that automation?

The conclusion of this line of reasoning leads to the recommendation that two critical areas of research be continued: (1) the study and modeling of information dependencies, vulnerabilities, and notions of value in automated decision making processes, and (2) the better understanding and modeling of patterns of human trust in automation. A case study framework would be motivational for this work, and if more than one case study could be defined, then the examination of the potential reuse of knowledge about critical information dependencies and values could be conducted.

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GLOSSARY

ATR	Automatic Target Recognition; Aided Target Recognition
B.C.U.	Binary Choice Unit
CI	Counterintelligence
COA	Course(s) of Action
COMSEC	Communications Security
COMPUSEC	Computer Security
C2	Command & Control
C2W	Command & Control Warfare
C4I	Command, Control, Communications, Computers & Intelligence
C4ISR	Command, Control, Communications, Computers, Intelligence, Surveillance & Reconnaissance
DBA	Dominant Battlespace Awareness
DD	Doctrine Document
DF	Data Fusion
DISA	Defense Information Systems Agency
DM	Decision Maker
DME	Decision Maker Effectiveness
DoD	Department of Defense
ECM	Electronic Counter Measures
EI	Effectiveness of Information
EV	Expected Value
EW	Electronic Warfare
HCI	Human Computer Interaction
He	Hypothesis Evaluation
Hg	Hypothesis Generation
HO	Human Operator
Hs	Hypothesis Selection
ID	Identification

INFOSEC	Information Security
IPB	Intelligence Preparation of the Battlespace
IW	Information Warfare
JAG	Judge Advocate General
JCS	Joint Chiefs of Staff
JDL/DFG	Joint Directors of Laboratories/Data Fusion Group
KB	Knowledge-Based
KBS	Knowledge-Based System(s)
KF	Kalman Filter
LOS	Line of Sight
MAU	Multi-Attribute Utility
MB	Model-Based
MIM	Mixed-Initiative Model
MOP	Memorandum of Policy
NAV	Navigation
OB	Order of Battle
OO	Object-Oriented
OPSEC	Operations Security
PF	Probability of False Alarm
PSYOP	Psychological Operations
RECCE	Reconnaissance
RL	Reinforcement Learning
R/M	Recognition/Meta-Cognition
RPD	Recognition-Primed Decision
SA	Situation Awareness
SHOR	Stimulus-Hypothesis-Option-Response
Ss	Subject(s)
USAF	United States Air Force
VI	Value of Information

DEFINITIONS

Binary choice unit (BCU): unit of information in terms of a deterministic two-choice situation.

Diagnosticity: the ability of a datum/piece of information to enable the ability to discriminate between alternative states of nature (situations).

Genotypes:

Index of determinism: a metric, ranging over (0,1-1/m) for m possible course of action, that measures the amount of determinism in a decision state; this metric ranges from (0) when all COA's are equally likely to (1-1/m) when a single COA can be deterministically selected

Netwar: covert, aggressive, hostile activities typically employing computer-based techniques used to both penetrate, with malicious intent, computer and computer network systems.

Phenotypes:

Purposeful state: a state of a decision maker wherein an intent to make decisions by selecting courses of action exists (with a purpose, *i.e.*, with expectation that the selected course of action makes progress toward a specified goal); this state also requires that alternative courses of action are not equally efficient in moving toward goal achievement.

Relational information: that information which aids in refining models of relationships among structural components (of the decision model as reflected in the decision matrices herein).

Semiotics: the theory of signs and symbols.